MELANOMA DETECTION USING CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

Melanoma is one of the most prevalent and severe skin cancer disorders, being difficult to identify and creating major difficulties once it has progressed deeper. Melanomas come in a variety of forms, sizes, and colours, making it difficult to give complete warning indications. Although melanoma is normally treatable in its early stages, if it is not treated, it can spread deeper into the skin or other regions of the body, making treatment more difficult and eventually fatal. As a result, early detection of melanoma is critical. Neural Networks have made great progress in this sector, allowing melanomas to be detected using numerous previously acquired patterns while dealing with bigger datasets than a human specialist can handle. In our work, we analyzed different models for detecting melanomas to select the most accurate method for this purpose.

Keywords: *Convolutional neural networks, skin cancer, melanoma, inception, efficient net.*

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1. INTRODUCTION

Detecting signs of skin cancer is a severe problem worldwide and is an ongoing task demanding state of the art technologies to fulfil and to make relevant progress in clinical diagnostics. Detecting melanomas accurately on human skin among the many types of pigmented lesions would be one of the most significant steps towards better healthcare. For this very reason, in our work, we set a goal to design and implement a method for analyze and compare existing solutions for image recognition that could be used for melanoma detection and evaluate the results to be able to select the most accurate algorithm. To achieve this, we gathered relevant and state of the art studies and papers and processed these to rely on them when designing our system. Melanoma, the most serious type of skin cancer, develops in the cells (melanocytes) that produce melanin — the pigment that gives your skin its color. Melanoma can also form in your eyes and, rarely, inside your body, such as in your nose or throat. Melanoma accounts for only about 1% of all skin cancers but causes the great majority of skin cancer-related deaths. It's one of the most common cancers in young people under 30, especially in young women. Melanoma incidence has dramatically increased over the past 30 years. It's widely accepted that increasing levels of ultraviolet (UV) exposure are one of the main reasons for this rapid rise in the number of melanoma cases. Predicting the melanoma in early stage which prevents the death rate. With our project we predict the melanoma by using two models IncepetionV3, Efficient Net B0 and finding the accuracy of the models. Melanoma detection is done by physically examine the skin tissue, by removing a sample tissue for testing (biopsy) which takes lot of time to detect. Late detection cause server problems. With help of machine learning models, we detect fast and accurately. In our project we use only two CNN models.

2. LITERATURE SURVEY

Melanoma is a type of cancer that originates from melanocyte cells, in most cases from the epidermis. [1][2] In case of detection at an early stage the 5-year related survival rate is 90%, which may be decreased to 9-15% by a delayed treatment started at tumor stage IV. [3][4] Therefore it is of high importance for early detection so that the prospects of a cure can be significantly favorable [5][6][7]. Dermoscopy in clinical practice is widely used for melanoma detection. The diagnosis is based on some specific morphological features of the mole, such as symmetry, border irregularity, colour variegation, [8] irregular dots of pigment, irregular peripheral extensions, a blue-white veil, and other specific irregular patterns [9]. This makes it possible to use pattern recognition techniques. In 1994, an artificial neural network was proposed for epiluminescence microscopy pattern analysis of pigmented skin lesions, which was amongst the pioneers of utilizing Artificial Intelligence for skin cancer detection solutions. In this study, 88% of the test set of pigmented skin lesions were diagnosed by human experts and 86% by ANN. [10] In another study, where a mobile application was developed for a similar purpose, 129,450 pictures were used with 2,032 different types of diseases, and a model was built with end-to-end training, to make it possible for users to recognize their lesions using this application. [11] Today AI performs better than dermatologists in melanoma detection. In many machine learning algorithms, it means a great disadvantage that the algorithm expects future data to be the same feature space and have the same distribution. This is not the case in most of the real-world applications, and to address this issue, transfer learning has emerged as a new learning framework. [16]

3. IMPLEMENTATION

3.1 DATASET

The HAM10000 ("Human Against Machine with 10000 training photos") dataset, which was produced exclusively for academic machine learning objectives, was the only open-source melanoma database available to us. This dataset contains 10,015 dermatoscopic images of benign and malignant moles, making it a typical sample of significant diagnostic categories. Pictures and meta-data were collected over a 20-year period, after which they processed the data, consolidated the diagnoses, and produced seven general groups of these dermatoscopic images. These general classes were designed specifically to allow the use of these photos as a benchmark dataset for both human specialists and machines in the diagnosis of pigmented lesions. These seven classifications account for more than 95% of all pigmented lesions seen in clinical practice. The lesions in these dermatoscopic photos are 600x450px at 96DPI and have been upgraded with hand histogram tweaks to improve contrast and color reproduction. Moreover, half of the images in this dataset were verified by pathology, and the remaining cases received ground truths from expert consensus or in-vivo confocal microscopy, resulting in an assured diagnosis in all cases. In our scenario, we must identify melanomas in these dermatoscopic photos. Just 1113 photos depict melanomas, accounting for 10% of the whole dataset. Although we worked with other lesion types to be able to differentiate melanomas from those photos, this is a substantially lower number, given that we also required a separate dataset for training and testing.

3.2 IMAGE PREPROCESSING

Because our goal was to detect only images containing information about melanomas, we performed a binary categorization on the HAM10000 dataset, using the labels ‘melanoma' for malignant melanoma and 'others' for all other lesions, which included actinic keratoses, basal cell carcinoma, benign keratosis, dermatofibroma, melanocytic nevi, and vascular skin lesions. Because the HAM10000 dataset only had 1113 photos of melanomas, we opted to employ data augmentation to improve the procedure. For this, we used the Picture Data Generator. Overfitting was also decreased as a result of data augmentation. We thought it was extremely critical to utilize a balanced dataset, thus we manually multiplied the melanoma picture dataset segregated for model training to create even datasets for melanoma and other types of pigmented lesions. We supplemented the data in two ways. We started by manually multiplying only the train dataset by the morphology of the melanomas, and then we employed an Image Data Generator for on-the-fly augmentation. Hand modifications included horizontal and vertical image flipping. Shape, symmetry, border irregularity, color spectrum, and uneven spots of pigment are some of the more important characteristics of a mole. As a result, we avoided using those values in the Picture Data Generator, which would have resulted in considerable variances in these attributes. Loading this produced dataset was initially impossible due to memory constraints, therefore we opted to load and train our models in batches. We utilized the flow_from_directory () function with a batch size of first 32, then 16 photos for this reason.

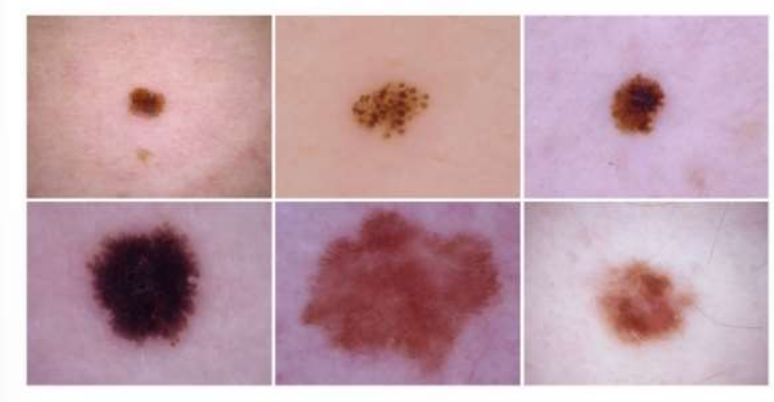

Fig -1: Melanoma (top row) and Non melanoma (bottom row) images

3.3 TRAINING

After preprocessing, the next stage was to determine which cutting-edge models may perform better in detecting our still very small collection of images. At first, we explored several methods of freezing the layers in order to attain better results. One possibility was to freeze all the base models. Hence, in both the EfficientNetB0 and InceptionV3 networks, we froze the base model, rendering it untrainable, and trained just the top layers, which included a GlobalAveragePooling2D layer, a Dense layer with Rectified Linear Unit (ReLU) activation, and another Dense layer with sigmoid activation. As a result, we obtained two models with separate, untrainable base models (EfficientNetB0 and InceptionV3) and the identical, trainable layers on top of this base model.

Another approach was to freeze certain basic model layers while leaving around half of them trainable. They did not produce the intended outcomes; therefore, we finally choose to keep every layer trainable. This arrangement seems to be the most effective. We made use of an Adam optimizer. We also opted to employ early halting and store the weights of the most accurate model. Initially, we utilized the same learning rate in both cases. Setting its value to 0.0001 in the EfficientNetB0 and IneptionV3 models. After some experimenting with the parameters, we found out that this number was excessively huge in the case of the InceptionV3 model, and to remedy this, we set its value to the tenth of the original size, to 0. 00001.We utilized the same batch size in both situations, which was 32 at first and 16 in the final parametrization. We experimented with the value of the 'step per epoch' parameter a little more. This parameter specifies the number of batch iterations to be performed before the model deems a training epoch complete. In general, the choice of this parameter may be critical in bigger datasets, or in our instance, when employing random data augmentations during the training process.

3.4 EVALUATION AND TESTING

We evaluated our models on the same set of test data because comparing them on different photos might lead to incompatibility between the two constructed models. We considered it important to utilize a balanced dataset, as we said in the image preprocessing section, therefore for testing, we also isolated a matching dataset, a total of 222 photos consisting of 111 melanoma and 111 non-melanoma images called 'others' in our instance. We obtained the following findings during the evaluation of the InceptionV3 model: the loss was 0.4101 with an accuracy of 82.43%. These were the best outcomes, during the EfficientNet-B0 model evaluation, the loss value was considerably lower, 0.3233, with a far superior 87.84% accuracy.

4. CONCLUSIONS

To summarize, we were able to effectively compare two convolutional networks with various basis layers for a more accurate picture recognition to identify melanoma malignum by modelling two convolutional networks with distinct base layers (a type of severe skin cancer). In our study, we constructed an EfficientNetB0-based model as well as an InceptionV3-based model with the identical top layers. This allowed us to determine whether base model is more accurate in detecting melanomas. The EfficientNetB0-based model proved to be more accurate and delivered better outcomes with our hyperparameter settings.

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