Dermoscopic Images Classification of Skin Lesion Using Densenet

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DERMOSCOPIC IMAGES CLASSIFICATION OF SKIN LESION USING DENSENET

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Abstract - Dermoscopic photography is used to diagnose skin cancer, often known as melanoma. Due to many elements, including poor contrast, varying tones, the presence of hair, fibres, and air, etc., such an assessment is challenging and time-consuming when looking for skin cancer with the naked eye. The method for skin lesion classification (SLC) proposed in this paper combines transfer learning, deep neural networks (DCNN), and picture augmentation. For the condition to be treated, early discovery is crucial. For the diagnosis of melanoma, skin lesions must be carefully examined.

Skin lesions can be found using dermoscopy, a non-invasive technique. It may be erroneous and subjective to classify lesions as benign or malignant manually using dermoscopic pictures. As a result, computer-assisted diagnosis (CAD) is crucial for aiding in the detection of melanoma. Segmentation, feature extraction, and classification are the methods employed in conventional computer analysis of dermoscopic pictures. Convolutional Neural Network (CNN), a deep learning technique, can be utilised to do skin categorization in place of employing several tools for segmentation, production, and classification. In this project benign keratinoid lesions, dermatofibroma, melanoma, basal cell carcinoma, melanocytic nevus, actinic keratosis, intraepithelial carcinoma, and vascular lesions are among the skin lesions that are detected and classified using a convolutional neural network based on DenseNet architecture. Our experimental investigation on lesion classification demonstrates that the suggested strategy can successfully classify different forms of skin cancer into distinct categories.

1. INTRODUCTION

The most dangerous kind of skin cancer is melanoma. The cause of 75% of skin cancer deaths is increased internal diffusion risk. Early identification makes therapy easier and reduces spread [1]. Therefore, it is essential to recognise malignant melanoma utilising dermoscopy pictures as soon as feasible. Melanoma is frequently characterised by changes in moles, such as a rise in size, colour, uneven margins, itching, and skin breakdown. It also happens infrequently on skin that looks normal.Annual melanoma cases have grown by 53% over the last decade, from 2008 to 2018, in part because of more UV exposure.

Melanoma, a dangerous type of skin cancer, has a greater chance of existence rate if it is detected early. The examination of the infected skin is the first step in a dermatologist's determination of a deadly lesion.

Due to various lesion types, a proper identification is crucial. Additionally, a doctor's professional experience and diagnostic accuracy are significantly correlated. Dermatologists diagnose melanoma with a 65%–80% accuracy rate without

any technical assistance. Deeper skin layers are visible throughout the recording because to regulated lighting and the application of a filter that lesseationns skin reflections. The accuracy of skin lesion diagnosis can be improved by another 49% with this technical support. Dermatologists can identify melanoma with an absolute accuracy of 75%–84% using a combination of ocular inspection and dermatoscopic imaging.

Recently, the discipline of machine learning has focused on the classification of skin lesions.

Automated lesion classification can help clinicians with their everyday clinical tasks by installing apps on mobile devices and providing easy access to critical diagnostics even outside of the hospital. The typical machine learning workflow of preprocessing, segmentation, feature extraction, and classification was employed by the bulk of research before to 2016. However, choosing the right features needs a significant amount of work and a high level of application-specific knowledge, particularly for feature extraction. Additionally, the earliest processing steps' mistakes and information loss have a significant impact on the categorization quality.

The type of cancer that affects the skin is skin cancer. DNA is harmed when the epidermis, the outermost layer of skin, is exposed to UV light. Skin cancer is the outcome of the epidermis's aberrant cells growing out of control. These aberrant cells start to spread to other interior body areas over time. The two types of skin cancer that can be broadly categorised are non-melanoma skin cancer (NMSC) and melanoma. NMSC includes certain less prevalent skin cancers as well as basal cell and squamous cell carcinomas.

Clinicians use a device called a dermatoscope to visually inspect skin lesions. The four main parts of a dermatoscope are a magnifying lens, a non-polarized light source, a transparent plate, and a liquid between the instrument and the skin. This tool makes it possible to observe skin lesions without being hampered by reflections from the surface Clinicians use a range of ways to differentiate between benign and malignant melanoma based on the visual features of the detected skin lesion. The ABCD rule [2], pattern analysis, Menzie's method [3], and the seven-point check list [4] are a few examples of these methods. The approach that clinicians use most frequently is the ABCD rule, which stands for asymmetry, border irregularity, non-uniform colour, diameter greater than 6 mm, and evolving size and indicates several clinical criteria. Due to the fact that some melanoma photos do not adhere to this criteria and human diagnosis is time-consuming because of the great seeing resemblance between the two type of lesions. Only if the dermatologist is well trained can dermoscopy boost the diagnosis sensitivity of melanoma detection by 10% to 27%. Without sufficient dermatologist training, dermoscopy's diagnostic performance for early melanoma detection has an inverse relationship. Additionally, human visual inspection-based

disease diagnosis is arduous, subjective, and time-consuming, and it can lead to inaccurate and inconsistent results.

As a result, there is an increasing need for computer-aided diagnosis (CAD) systems that can handle all of these issues and provide a second opinion that will be useful for early disease diagnosis. These devices also aid in lowering the high number of unnecessary and expensive biopsy operations. Machine learning or deep learning-based techniques can be utilised to classify melanoma using CAD systems. Recently, convolutional neural networks (CNN) have excelled at a number of tasks involving the analysis of medical images [5]. CNN, which has the capacity to learn hierarchical features from unprocessed dermoscopic pictures, can be utilised for melanoma classification in place of low level handmade characteristics for melanoma recognition. Deep learning models may directly predict the type of skin cancer and are typically taught end to end, leading to a fully autonomous system with minimal human input. In this study, an end-to-end classification system called DenseNet architecture is employed to categorise skin lesions to its types. The work's primary objective is to teach the architecture and then to use evaluation metrics to analyse the network's performance for the same classification task.

2. LITERATURE SURVEY

As the time of melanoma detection increases, the risk of spreading of melanoma to other organs through the lymph increases thereby increasing the mortality rate. This risk can be reduced with the help of CAD techniques. Classification of melanoma using CAD systems include machine learning or deep learning based techniques which differ in the steps involved for the task. Machine learning based melanoma classification involve three major stages: categorization, feature extraction, and lesion segmentation. Before segmentation, the dermatoscopy images need to be pre-processed. Basic pre-processing procedures include eliminating varying lighting effects [6], converting the colour space, choosing the right colour channels [7], enhancing the selected colour channels [8], enhancing contrast [9], normalising colour variation brought on by image acquisition, smoothing the image, removing hair [10], and removing the vignetting effect [11]. A suitable combination of pre-processing procedures is necessary for accurate lesion segmentation.

Prior identification of type of noise or artifacts present in the image is necessary for proper selection of the pre – processing technique. But a generalisation of pre – processing techniques is not possible due to variation of artifacts in different dermoscopic images. After pre – processing only segmentation can be performed. Decomposition is the process of dividing the afflicted part of the epidermis from the lesion. Thresholding, region-based, and edge-based methods are three basic categories of segmentation techniques. Clustering [12], histogram thresholding [13], and adaptive thresholding are all parts of thresholding-based

segmentation. With a bimodal image histogram, or there is a better comparison between the wound and the epidermis, these methods give good outcomes for dermoscopic images. If approches from both zones combine, they are unsuccessful. Both the techniques [14] based on zero-crossings of the laplacian or gaussian function badly when there is a easy change between skin and injury and also without well-defined boundaries, resulting in leaking of contour through gaps in the edges. Multi-scale region growing is one strategy based on region. The multi scale region growth [15], modified fuzzy c-means [16], formation of several decision markov random field algorithm, and mathematical scope [17] are a few examples of region-based methods. They result over dispersion when the skin or wound region is formed. From the segmented region features are extracted that can characterize the samples. Skin lesion features used for classification include morphological features, colour and texture based features. Asymmetry, border irregularity, eccentricity and diameter forms the morphological features [18]. But these features will not recognize some moles with malignancy at early stages, such as malignant melanoma with diameter smaller than 6mm. Global characteristics can be calculated using the lesion area. including colour and texture features, but their values are tainted by the presence of bubbles and other artefacts [19].

This has an additional impact on classifier performance. The final stage is to develop a classifier to separate benign lesions from malignant melanoma by using these features. The most widely used classifiers include (SVMs), logical declining, decision trees, ensemble learners, k-nearest neighbours (k-NN) [21], and support vector machines (SVMs). such as AdaBoost. Advantage with these classifiers is that they can be trained with lesser amount of data. But their robustness to classification is low. Due to the significant intra-group and minimal inter-class variability in melanocarcinoma, the handmade characteristics based indicative act is still shown. Segmentation of a desired region or the classification of diseases are two examples of how CNN is used in medical pictures. Medical image segmentation processes like MRI, ventricle segmentation, and x-ray use CNN. CNN is used for diagnosis tasks such as tumour identification, tuberculosis diagnosis, lung cancer screening. There are several works that focus on end to end deep learning based melanoma classification such as deep learning ensembles [22], ResNet [23] etc.

3. PROPOSED WORK

A recently created deep learning algorithm called DenseNet is utilised to categorise dermoscopic images into benign and malignant. Dermoscopic image classification is carried out automatically without the use of complicated picture pre-processing or lesion segmentation. The proposed task entails evaluating how well this design performs when a variety of optimizers are chosen in order to determine the optimum optimizer for the network.

SYSTEM Requirements

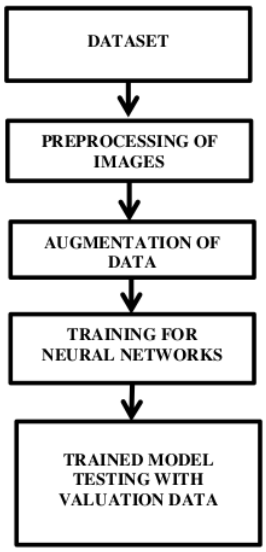
Software Employed:

- Operating System : Windows 7 / 8/ 10
- Programming : Python
- ATA : Anaconda, Notebook

Hardware Employed:

- Processor : Intel core i3
- Ram : 8 GB
- Hard Disk : 120 GB

4. FLOW DIAGRAM



5. PROCESSES IN CNN

Dataset gathering

Starting with the training phase and continuing through the evaluation of the performance of recognition algorithms, appropriate datasets are needed at every stage of skin lesion identification. The Internet was used to download each and every image used in the collection.

Preparing and Labeling Images

Images downloaded from the Internet came in a variety of formats with varying resolutions and levels of quality. Final photos that were going to be utilised as a datafile for a deep neural network classifier were preconditioned to improve feature extraction. Additionally, all of the photographs were manually cropped as part of the image preparation process in order to highlight the region.

Augmentation Process

Basic goal is to increase the dataset and somewhat distort the pictures as they aid lowering the overfitting during the learning step. Augmentation of image data is a procedure for fake increasing the capacity of a learning dataset by giving changed versions of the data file photographs. The capability of fit models to conclude what are the new techniques that can be implemented to improve the quality of the new images can be taught by deep learning neural network models on data.

Training a neural network

It has as its major objective teaching, it the characteristics that set a standard apart from all the others.So, the probability that the grid will advance itself by using more enhanced photos.

Testing the Trained Model Using Valuation Data

The trained grid is finally utilized inorder to identify disease by computing the given photos from the valuation dataset, and the results are processed.

6. PARAMETERS AND RESULTS

The training is done on the consisting of 7 classes of images. Basalioma , pigmented nevus, solar keratosis, endometrial intraepithelial carcinoma, benign fibrous histiocytomas of the skin, and birthmarks are the classes in this categorical classification issue. The dataset is first randomised, after which 80% of the photos are used for tutoring and the rest 20% for evaluation. The collection includes of images in various sizes. To be provided to the network, these photographs are scaled to a standard size.All these images are normalized by dividing the image pixels by 255 before giving to the network. The learning rate is initialised to 0.001. The programming is done using python language on Jupyter notebook platform.

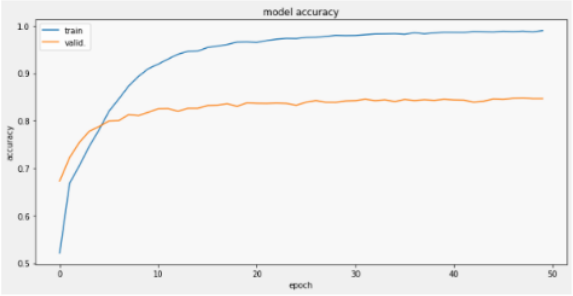


Fig1 : Model Accuracy

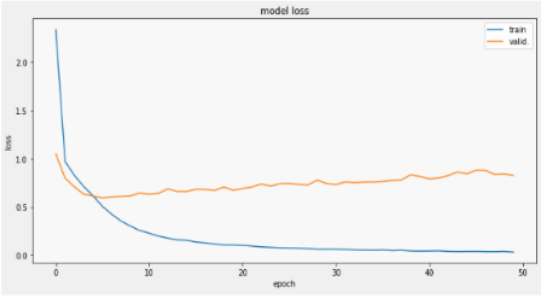


Fig2 : Model Loss

Once the network is trained using the DenseNet its classification performance is evaluated using the validation dataset. From the metrics it is clear that DenseNet model trained with Adam optimizer obtained the accuracy greater than 90% for melanoma classification. Using this architecture prediction of new dermoscopic images is done. Depending on the type of the image the network

predicts it into one of the 7 classes.

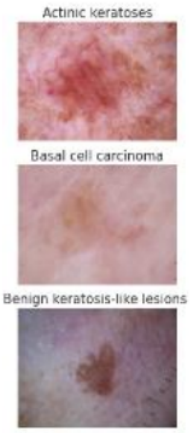


Fig 3: Predictions made using the network

7. CONCLUSION

In this paper, a DenseNet-type melanoma classification method is investigated. Dermoscopic pictures are categorised into 7 types using the freshly created deep learning framework DenseNet. Three optimizers are used to train the DenseNet architecture on the ISIC data set. Without using intricate picture pre-processing, lesion segmentation, or feature extraction, melanoma classification is carried out. The performance of the classifier is evaluated using threshold and ranking criteria. The evaluation metrics show that for the job of lesion classification, the DenseNet architecture trained with the Adam optimizer performs better than the network trained with the other two optimizers. Future potential for this network could be used for more diagnostic procedures in medicine.

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