Hong Kong International Journal of Research Studies, ISSN: 3078-4018
Volume 2, Issue 2, July-December, 2024
Available online at: https://octopuspublication.com/index.php/hkijrs

System Design for Image Segmentation of Skin Lesion Utilizing Deep Learning Techniques

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ABSTRACT

The detection and segmentation of skin lesions play a crucial role in the early diagnosis of skin diseases, including melanoma, which is one of the most aggressive forms of skin cancer. Accurate segmentation of skin lesions in dermoscopic images can significantly improve the performance of diagnostic systems. This paper proposes a deep learning-based system designed for the segmentation of skin lesions in medical images. The system utilizes Convolutional Neural Networks (CNNs) and advanced architectures like U-Net, known for their effectiveness in image segmentation tasks. The model processes dermoscopic images by automatically identifying and segmenting the lesions from surrounding skin tissues, overcoming the challenges posed by varying lighting, skin tones, and lesion boundaries. The approach leverages pre-trained deep learning models, fine-tuned for skin lesion segmentation using a dataset of labelled dermoscopic images. Data augmentation techniques such as rotation, scaling, and flipping are applied to mitigate overfitting and improve generalization. The system achieves pixel-wise segmentation accuracy and a high Dice Similarity Coefficient (DSC), ensuring robust performance across different datasets. Additionally, the system integrates post-processing steps such as morphological operations and conditional random fields (CRFs) to refine the segmentation mask. The proposed method demonstrates significant improvements in segmentation accuracy compared to traditional image processing techniques, making it a valuable tool for clinical settings. This deep learning-based system can be seamlessly integrated into telemedicine applications and assist dermatologists in diagnosing skin lesions, enabling faster and more reliable identification of potential malignancies.

Keywords – Segmentation, CRFs, Accuracy, DL, CNNs

INTRODUCTION

The skin is one of the components that is both the most noticeable and the most significant. Additionally, it serves as a fertile setting for the development of infectious illnesses, viruses, and germs. There is a wide range of skin problems that fall under this category, such as acne and atopic dermatitis. The condition of the skin can only be addressed if it is discovered at an early stage. Dermatologists are able to observe superficial skin changes using a technique called dermascopy, which is common knowledge. By using strong light and polarization, it brings about a reduction in surface reflectance. A significant number of people all around the world struggle with skin conditions. Melanoma is one of the most serious skin illnesses, especially when compared to other skin conditions. It is less likely that the sickness may spread to the skin if it is checked out during the earlier stages. A further point to consider is that people might display a wide range of main and secondary skin types. The two primary classifications of these abnormal cell growths are abnormal skin tumours that are benign and those that are cancerous. When they are initially discovered, benign lesions are composed of normal cells that are slightly in conflict with one another. On the other hand, malignant or cancerous tumours are composed of cells that multiply in an uncontrolled manner and finally succumb to death. The automated inspection of clinical photographs, which is related with image class names, is an example of an application case that may be found in a number of different domains of machine learning. In the field of artificial intelligence, a CV device is used to bring about the automation of a system via the utilization of visual images. A few examples of automated photo analysis technologies include detection, identification, and segmentation. One of the key goals of segmentation is to separate the themes from the photos that serve as examples. On the other hand, characteristics are used during the identification step identify problems with the image. Detection extracts multi-level attributes, which are then categorised using supervised learning techniques (Acharya et al., 2019).

Research that predicted CAD models was carried out by Fernandes and colleagues in the year 2016. Colour constancy framework and skin disease analysis are the two most advanced computer-aided design systems. The pre-processing, segmentation, feature descriptor extraction, and classification processes are the four basic components that make up a computer-aided design system. When it comes to clinical image processing, the gold standard is to bring the lesion to the forefront of the raw picture. By doing so, the lesions may be isolated from one another more readily. A better image of a tumor's form and characteristics might be obtained by using an optimal segmentation algorithm. Thus, classifying skin tumours is highly dependent on feature separation. There is still some problem with these models incorrectly identifying objects, despite how well they divide and categorize. Existing literature demonstrates the concept of deep models for various CV approaches. The principle behind it is to improve the classification approach by creating several feature vectors. The decision requires a large amount of training data. The CNN class includes these deep structures. They include many large layers, such as convolution, pooling, ReLU, and FC. These tiers transform raw data into actionable characteristics. The primary goal of this research project is to develop a dermoscopy image tumour detection system that uses deep learning for segmentation and classification. The reason for this is the efficacy of DL models. Several research aims, detailed below, served as the basis for organizing the whole study endeavor.

- **GOAL I:** The purpose of this study is to review the literature on computer-aided diagnosis (CAD) models for skin lesion categorizations and diagnosis using dermoscopy pictures.

- **GOAL II:** A new MN with GNB and SVM models, which will be referred to as MN-GNB and MN-SVM, will be developed for the purpose of dermoscopic skin lesion identification and classification.

- **GOAL III:** For the purpose of skin lesion diagnosis, to present a DTL model that is built on the VGGNet-19 Network and incorporates XGBoost and LDA models referred to as VGG19-XGBoost and VGG19-LDA.

- **GOAL IV:** present an EDLS method for skin lesion identification that uses the Xception model, then LR and RF classifiers, specifically Xcep-LR and Xcep-RF,

LITERATURE REVIEW

Research on the segmentation of skin diseases has made use of DL models that are already in existence. The DL technique has received a significant amount of interest from the medical imaging domains, notably those dealing with brain MRI and breast ultrasound for the purpose of cancer prediction. U-Net, one of the most renowned DL approaches used in biological imaging research, was recently published by Ronne berger et al. (2015). U-Net fully utilizes the annotated example photographs for model training by adding techniques like non-rigid deformations to the data. Because of these factors, U-Net seems to be the most effective method for enhancing the smaller biological datasets that are currently available. When it comes to the prediction and categorizations of skin cancer, developers have made tremendous progress by offering a number of deep learning algorithms. The authors Yu et al. (2017) suggested a two-step technique that makes use of a deep residual network differentiate and classify skin lesions respectively. By using this method, a more extensive network offers a number of different and beneficial traits to take into consideration. Last but not least, the event illustrated how hard it was to do anything. On the other hand, the two-stage structure and really deep networks need a significant amount of money. The purpose of the multi-stage FCNs that Bi et al. (2017) exhibited was to figure out how to divide skin cancers successfully. Through the use of multi-stage, focused coarse appearance learning, contemporary deep learning algorithms have been built for the purpose of classifying skin conditions.

Yuan and Lo (2019) described a convolutional neural network (CNN) for the purpose of developing binary masks acquire the knowledge necessary to differentiate between skin malignancies and dermoscopy pictures. Following that, the properties of the image were retrieved make use of a pixel-wise classification model for the purpose of classifying skin defects. In addition, a loss function may be lowered by training that makes use of the Jaccard distance. For every N, a grid search yields the hyper-parameters, and each N has 29 layers. Among their principal applications are the deconvolutionalization of pictures and the upsampling of images. Other colour space variables used for categorizations include hue, saturation, and brightness in laboratory settings. To produce reliable segmentation results, the ensemble technique employs CDNN, one of the fundamental algorithms. Lastly, this model demonstrates the optimal level of skin disease segregation. In their 2018 paper, Li and Shen demonstrated a deep learning method for classifying and separating big lesions using FCRN. By calculating the relative importance of each pixel relative to the image's edges, the LICU enhances the classification results. Specifically, the first rough maps were made using FCRN, which was trained on both actual images and images that had been altered and supplemented. Afterwards, distance maps are created using LICU. After that, feature maps are obtained by passing them through convolution, which improves the crude maps. This means that the average likelihood of advanced maps is what ends up being used for lesion categorizations.

To differentiate between different skin lesions, researchers Alvarez and Iglesias (2017) utilized ensemble regressions in conjunction with an iterative color-related K-Means grouping technique. There are several techniques that are utilized in this procedure, including the Jaccard score, feature extraction, color grouping, and photo pre-processing. For the purpose of training the regression system, the ISIC 2017 data set is utilized for both training photos and images that are an accurate representation of the world. The single area was used to collect a great deal of information, including the position, the average color, the hardness, the area, and the roundness of the object. For the purpose of estimating the division based on the Jaccard Index, the RF and SVR approaches are also utilized. Until we achieve the number of groups that have a Jaccard score that is statistically significant, we shall continue to proceed with our work.

In their 2018 publication, Ashour et al. described the Histogram-Based Clustering Evaluation. Neutrosophic C-Means Clustering, also known as HBCENCM, is a technique for the segmentation of skin diseases that follows the clustering methodology. The HBCE technology truly shines when it comes to the process of aggregating the histograms of photos. The process of separating skin lesions using NCM clustering is simplified by the utilization of a predetermined number of groups. Therefore, the actual NCM model is unable to compete with the newly developed HBCENCM method, which employs a horizontal-vertical strategy to differentiate between different skin lesions. Estimates obtained through the utilization of the ISIC archive data set indicate that this method has performed significantly better in terms of separating lesions than the DL algorithms that were examined. Fuzzy image classification and histogram thresholding were utilized in another work conducted by Garcia-Arroyo and Garcia-Zapirain (2017) differentiate patients with lesions. With the help of the NCM app and a customizable area that was visible in dermoscopy images, Guo et al. (2018) were able to categorize skin lesions into distinct groups. The Shearlet Transform (ST) mapping into the neutrosophic set domain was the first method that was utilized visualize skin lesions. Therefore, determine the lesion segmentation, the NCM clustering method and the adaptive area expansion method were utilized.

METHODOLOGY

The whole of the educational system may be broken down into three main stages. A demonstration of the MN-GNB and MN-SVM models for the detection of skin tumours is shown in the first part. Both the VGG19-XGBoost and the VGG19-LDA models are used in the second part for the purpose of identifying skin flaws. In the concluding stage, Xcep-LR and Xcep-RF are used to conduct the classification of skin cancers.

Phase I: Models for SVM and MN-GNB

An innovative DL-based computer-aided diagnosis (CAD) model is proposed in this part with the intention of identifying and classifying skin tumours that may be detected subcutaneously. The recommended technique includes a number of different procedures, some of which include preprocessing, segmentation, feature extraction, and classification for example. The removal of noise and the determination of ROI are the primary goals of picture pre-processing. Additionally, the method of image segmentation known as Density-based Fuzzy C Means (DFCM) is used in this process. The MobileNet model is also used as a feature generator gain a collection of feature vectors that are of great value. Additionally, the GNB and SVM classification models are included into MobileNet's final layer facilitate the development of the MN-GNB and MN-SVM methods to the categorisation of skin cancer conditions. determine whether or not the MN-GNB and MN-SVM models that we have presented are effective, we will carry out a series of tests using the ISIC dataset, which is the standard in the industry.

Phase II: A Model for VGG19-XG Boost and VGG19-LDA

In this step, a new segmentation and classification model that is connected to DTL is suggested as a means of locating skin cancers via the use of dermoscopy pictures. For the purpose of pre-processing picture noise reduction, the BF approach is often used. The pre-processed picture is then disassembled using the Grab-chop method, which does not let any modifications to be made to the image under any circumstances. Through the use of the VGGNet-19 Network, feature vectors that are not only beneficial but also founded on DTL are retrieved. Lastly, the XGBoost and LDA models are used ascertain the names of various different classes of skin tumours. A battery of tests was performed on the ISIC dataset guarantee that the suggested model would generate valid analytical findings.

Phase III: Xcep-LR and Xcep-RF Model

In this stage, EDLS skin damage research that includes a forecast is demonstrated, and this is made possible by the successful DL approaches. The DL model is utilized in this particular model for the purposes of classification segmentation operations. The separation of the points is accomplished by the utilization of an EDLS method that makes use of Mask RCNN and Full-resolution Convolutional Network (FrCN). It is possible to obtain functions by utilizing the Xception model. Using LR and RF models, the final stage consists of determining the appropriate names for the classes. The suggested model is put through multiple iterations of testing on the ISIC dataset guarantee that it is accurate.

IMPLEMENTATION

Python 3.6.5 with the following packages added to the installation: carry out the models that are defined in this study, the following technologies are utilized: keras, numpy, matplotlib, sklearn, pillow, opencv-python, and tensorflow (GPU-CUDA Enabled). The components that are used to power it are a hard drive with a capacity of 1 terabyte, 16 gigabytes of random-access memory, an i5-8600k central processor unit, and a graphics card with a capacity of 4 gigabytes of GeForce 1050 Ti. The standard ISIC dataset, which may be accessible at https://www.isic-archive.com, will be used in a number of experiments provide support for the diagnostic results that are provided by the presented models. The collection contains 318 dermoscopy photos, each of which has its own label that is distinct from the others. The resolution of the images in the collection is 640 pixels wide by 480 pixels tall. In all, there are 78 photos belonging to the Solar Lentigo class, 51 representing the Melanoma class, 43 belonging to the Nevus class, and 37 belonging to the BCC class. Twenty-one photographs are included in the Angioma class, whereas forty-six images are included in the Nevus class. Figure 3.1 presents a selection of the example photographs that are included in the collection.

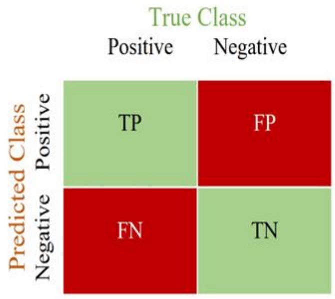

Figure 1 Images of Skin Lesion Samples

The performance of a "classifier" or "classification model" is often satisfactory when used to test data sets in which the real value is known. A table, often known as a confusion matrix, is used to illustrate this notion. The confusion matrix is a resource that provides information on the existing and projected categories that are used by a classification model effectively classify objects. On the basis of the information included in the matrix, a great number of individuals make accurate judgements regarding the performance of similar systems. Figure 3.2 depicts the confusion matrix that is generated by a classifier that uses two classes. For the purpose of determining whether or not the model is effective, tests such as True Positive (TP), True Negative (TN), False Negative (FN), and False Positive (FP) are used. In addition, it is necessary to possess accuracy, sensitivity, and specificity. In this particular scenario, we might compute it by using the formula that is as follows:

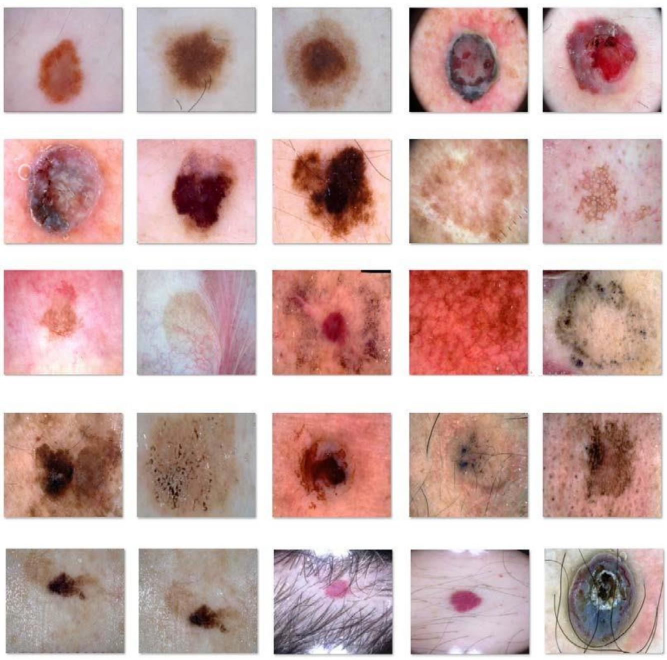

Figure 2 Confusion Matrix

There is a possibility that a real disease may take place, and the prediction may be correct at times. Due to the fact that they are not sick, it is possible that someone was aware that they would not get ill eventually. Despite the fact that it is able to identify it, they are not really sick, according to FP. A negative prediction indicates that the illness is present, as indicated by the letter FN. It is for this reason that the mistake is referred to as a "Type I error." An additional term that may be used to refer to this sort of problem is a "Type II error."

CONCLUSION

The research approach, the proclaimed goals of the study, and the particulars of the experiment are all discussed in this portion of the report. The section 3.2 of this paper provides a comprehensive explanation of the research goals that will be pursued. The section 3.3 provides an illustration of the three components that make up the overall study design. Within the last part (3.4), the specifics of the experimental approach are described in exhaustive detail. Detailed information on the dataset the evaluation criteria can be found in these. MN-GNB and MN-SVM are both created in the next chapter, which may be found here. Both GNB and SVM are used in these two unique MN models, which allow for the detection and classification of microscopic skin lesions**.**

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