Skin Lesion Segmentation Detection Using U-Net Architecture

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Abstract

Skin tumours account for the bulk of malignancies worldwide. The two main categories of skin cancer are melanoma and nonmelanoma. Examples of nonmelanoma skin cancer include basal cell carcinoma and squamous cell carcinoma. The two biggest risk factors are having fair skin and frequently being exposed to UVB rays. The initial and most crucial step in computer-based skin cancer diagnosis is segmentation because other activities heavily rely on correctly segmented lesions. In the segmentation of skin cancer disorders, deep learning with convolutional neural networks (CNNs) was reported as a unique technique that offers effective disease segmentation. The suggested approach makes use of a CNN that has been trained using a publicly available dataset of photos representing a skin cancer condition together with the corresponding mask images. In order to diagnose diseases, it was shown that neural networks can record the colours and textures of lesions particular to those diseases, which is similar to human decision-making.

Keywords: skin tumours; CNN; U-net architecture ;

1. Introduction

Deep Learning (DL) has recently demonstrated superior performance in a variety of bio-medical image processing modalities. For classification, segmentation, and detection tasks in computational pathology and medical imaging, a number of DL architectures have been developed. Melanoma, the most serious form of skin cancer, spreads quickly without treatment. Melanocytes, the cells that produce the pigment melanin, which gives skin its colour, are where it begins. It can enter the bloodstream, travel to the dermis, the skin's base layer, and then spread to other body parts. Skin-based cutaneous melanoma is the most prevalent kind of melanoma. In order to successfully treat melanoma, it is best to catch it early since it can occasionally start as a mole. The major goal of the present research is to use deep learning-based automatic skin lesion segmentation to improve the classification performance of melanoma. Dermoscopy images can help medical professionals make an early diagnosis of melanoma. a some of the terms used in the prediction field.

Nonmelanoma [1] - A category of tumours that progressively manifest in the top layers of the skin are referred to as skin cancer.

Basal cell carcinoma [2] - a specific kind of skin cancer that starts in basal cells. As old skin cells die, basal cells regenerate new ones. Reducing your exposure to the sun can help stop these cells from developing into cancer.

Squamous cell carcinoma [3] – skin's middle and outer layers, which are made up of squamous cells, are the site of a prevalent type of skin cancer.

2. Related Work

Dermatologists frequently use follow-up dermoscopic pictures of skin lesions to diagnose or rule out early melanoma. Yet, single time point photos of lesions are used to construct current algorithms for early melanoma diagnosis [4-15]. Borderline cases may be misdiagnosed if the temporal and morphological alterations of lesions are ignored. In this study, utilising successive dermoscopic pictures, we suggest a system for automated early melanoma diagnosis. A methodology for early melanoma diagnosis utilising consecutive dermoscopic pictures to simulate lesion progression is described in certain research works[16-

19]. The authors proved the value of include temporal cues in melanoma diagnosis and show that the suggested method is superior to previous sequence models at collecting lesion changes from serial pictures[20][21] for early melanoma identification. Some of the drawbacks are focused on Accuracy which is low and only classification of the cancer is predicted.

3. Proposed System

A challenging component of the pattern recognition system is image segmentation. Image segmentation is the process of dividing an image into several regions. It can make use of a variety of components with high-resolution characteristics, including pixels, texture, and shape attributes. Data collection is the most effective way to gather and analyse information from many sources. The segmentation of an image using a CNN algorithm is the proposed approach. The datasets of unmasked and masked photos are utilised to train the segmentation algorithm. The data is trained using the CNN algorithm's U-Net architecture, and a model is then built. The segmentation of the image is completed by using the model. Skin Cancer segmentation is one of the major factors in our healthcare domain. There are a lot of skin diseases that are actively present in the world. So, classification process as shown in Figure 1 is challenging. Hence, this system can easily segment the affected area. Some of the features of proposed system are as follows.

- Predicts the affected area accurately.
- Accuracy will be improvised.
- Deployment of the project will be implemented.

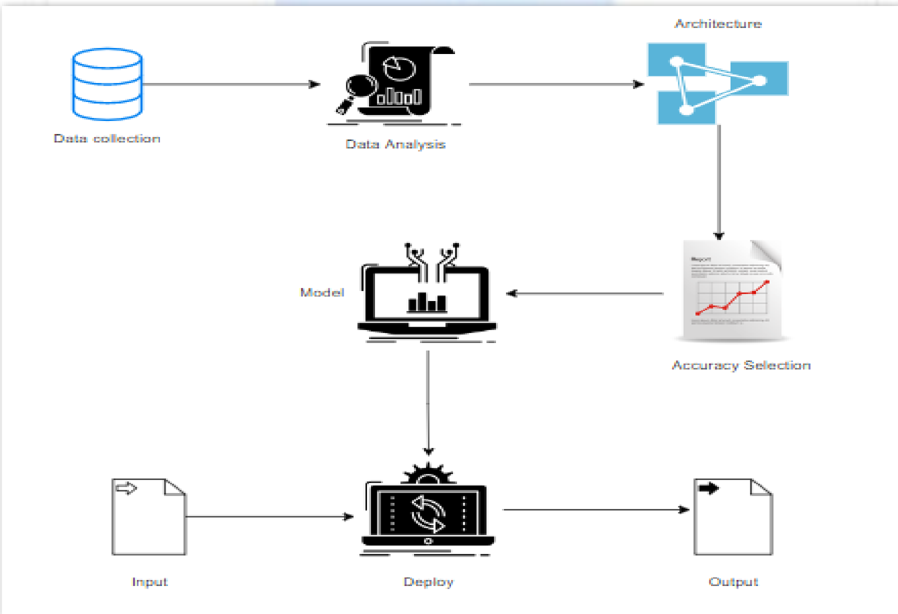


Figure 1 System Architecture

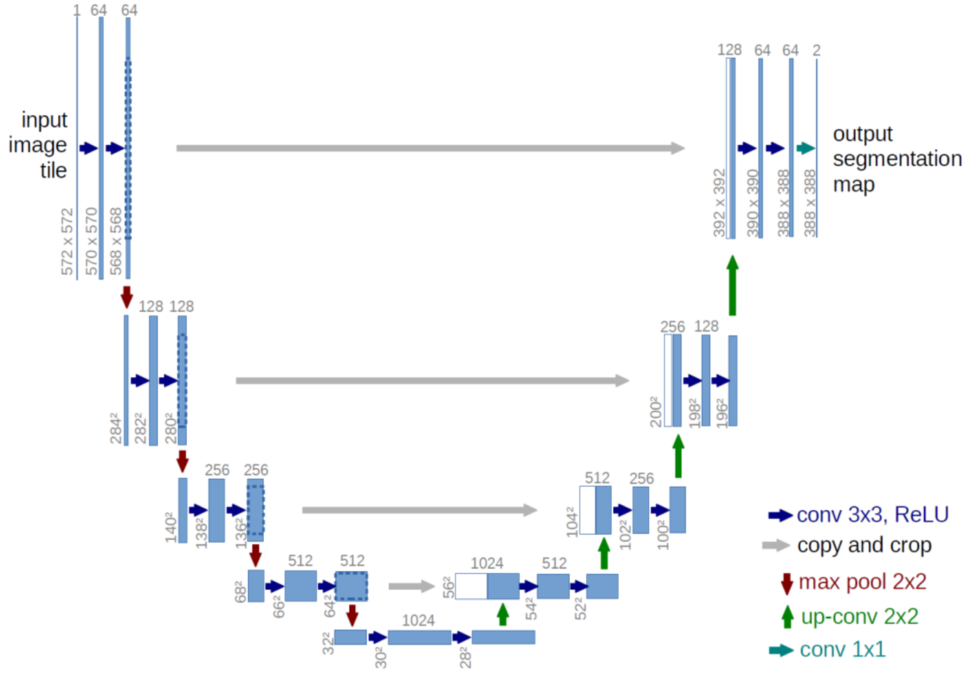
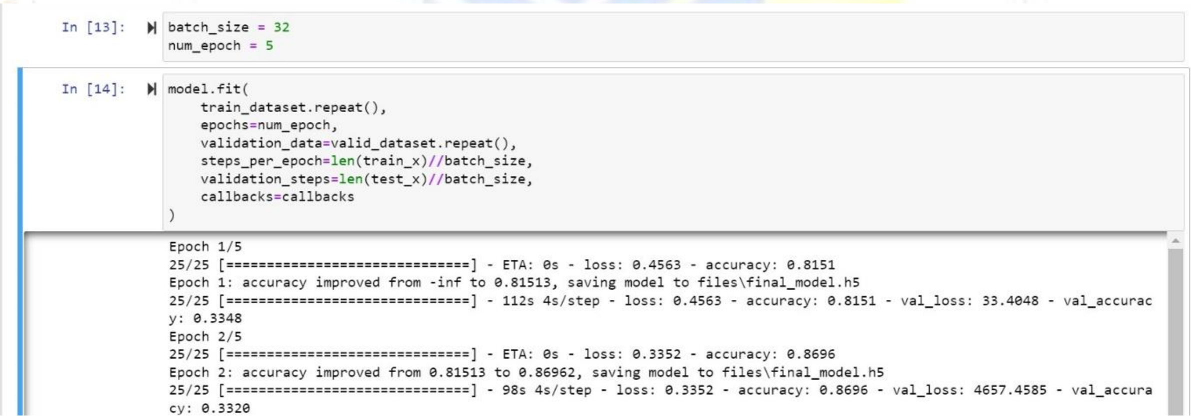


Figure 2 Architecture of U-net

A modern GPU can quickly compute the segmentation of images with a size of 512X512 using this U-Net architecture. This architecture has undergone numerous variations and alterations as a result of its extraordinary success. The recurrent and residual convolutional U-Net (R2-UNet), LadderNet, U-Net with attention, and U-Net with residual blocks or blocks with dense connections are a few of them as shown in figure 2.

4. Results and Discussion

The batch size is given as 32 and number epoch (i.e., the number of forward propagation and backward propagation) is 5. The accuracy and loss of the given data set is been shown in figure 3, figure 6 and figure 7. The figure 4 and figure 5 depicts on the normal dermoscopy images and masked images for segmentation process.The x axis in figure 6 is accuracy plot and y axis is number of epochs. Figure 7 depicts on loss model where x axis is loss and y axis is number of epochs.

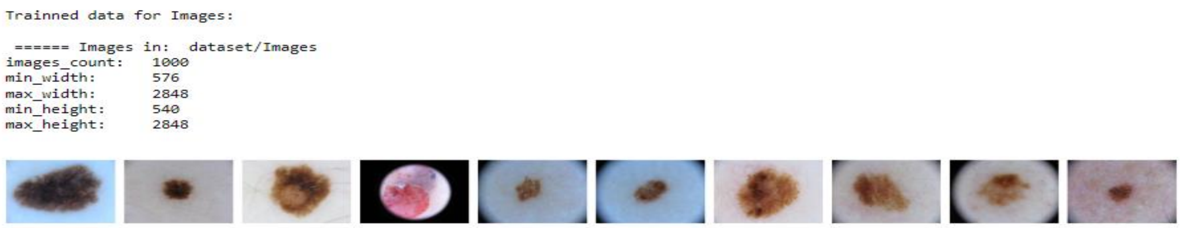


```
In [13]: batch_size = 32
         num_epoch = 5

In [14]: model.fit(
             train_dataset.repeat(),
             epochs=num_epoch,
             validation_data=valid_dataset.repeat(),
             steps_per_epoch=len(train_x)//batch_size,
             validation_steps=len(test_x)//batch_size,
             callbacks=callbacks
         )

Epoch 1/5
25/25 [==============================] - ETA: 0s - loss: 0.4563 - accuracy: 0.8151
Epoch 1: accuracy improved from -inf to 0.81513, saving model to files\final_model.h5
25/25 [==============================] - 112s 4s/step - loss: 0.4563 - accuracy: 0.8151 - val_loss: 33.4048 - val_accurac
y: 0.3348
Epoch 2/5
25/25 [==============================] - ETA: 0s - loss: 0.3352 - accuracy: 0.8696
Epoch 2: accuracy improved from 0.81513 to 0.86962, saving model to files\final_model.h5
25/25 [==============================] - 98s 4s/step - loss: 0.3352 - accuracy: 0.8696 - val_loss: 4657.4585 - val_accura
cy: 0.3320
```

Figure 3 Accuracy Parameters



```
Trainned data for Images:

 ====== Images in:  dataset/Images
images_count:    1000
min_width:       576
max_width:       2848
min_height:      540
max_height:      2848
```

Figure 4 Sample Images

Figure 5 Masking Process for segmentation

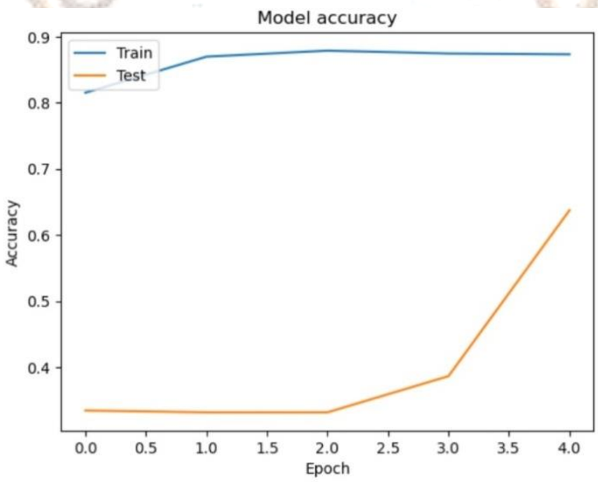


Figure 6 Accuracy Model

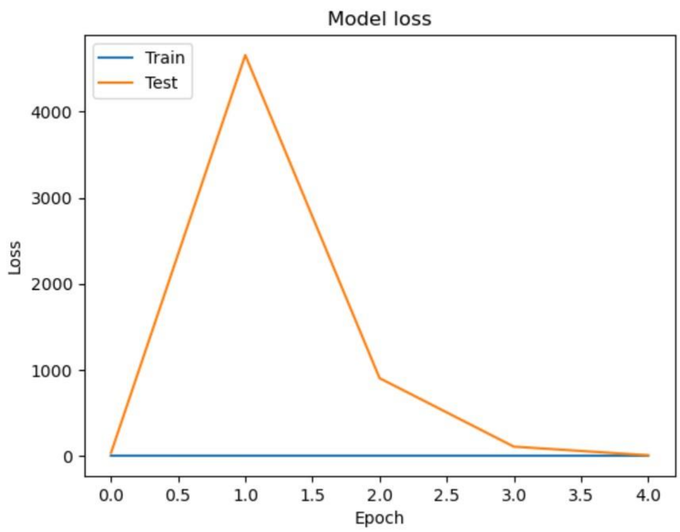


Figure 7 Loss Model

.6. Conclusion

Image segmentation is a crucial computer vision job with a wide range of applications in the medical field. Here, we examine the available data and train the data. From the taught architecture, the best architecture is chosen and turned into a model. The Django framework uses the construction model to segment the skin cancer image. The following methods can be used to increase the network's accuracy even more. The data can be generalised using the right pre-processing methods. To increase the accuracy of the data, data augmentation can be used.

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