Breast Cancer Detection using Image Segmentation

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Abstract

Breast cancer is the most prevalent kind of malignancy in women, and diagnostic systems that apply artificial intelligence algorithms for breast imaging have shown positive results. Two methods that increase the precision of detecting breast tumors from mammography images are a multiclass support vector machine model and a deep convolutional neural network (DCNN) using K-means clustering. To accurately diagnose breast tumors, the pectoral muscle (PM) border must still be distinguished from the rest of the breast tissue. By merging the transfer learning model with a number of pre-trained CNN structures, this research offers an Ensemble-Net model for distinguishing the PM boundary from the rest breast region in mammograms. The segmentation procedure consists of 2 steps. According to the input, various regions of interest are formed in the initial phase and include the object.

Keywords

Sematic segmentation, deep learning, image segmentation, transfer learning, and case report

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1. Introduction

One of the types of tumors that develops and spreads in the breast tissues is a breast tumor. Women account for 99% of all cases of breast tumors. According to data from the World Health Organization (WHO), breast tumors are the most common malignancy among women and that occurrences are growing in virtually all of the nation's major areas, despite the fact that only a tiny percentage of risks may be removed by preventative measures. It is critical to make a breast tumor diagnosis as soon as feasible in order to optimize clinical outcomes. Effective and quick radiography exams are essential for the early detection and prevention of breast cancers [2]. To detect and diagnose breast cancers, a variety of screening techniques are available. Mammography, among other things, plays a crucial role in the accurate early diagnosis and treatment of breast cancers. Mammography, which examines the breast using low-dose X-rays, is frequently used to check for breast cancers. Anomalies and clusters of lesions are two crucial breast cancer-related features that mammography examinations can help find [3]. Mammograms are often indicated for a range of issues, including Monitoring for malignancies or deformities are the first two. The other two are treatment for breast abnormalities, a mammogram performed after a prior negative mammogram, and treatment for breast abnormalities. Divvying up a picture into its many components is called image segmentation. Image segmentation may be done using a variety of different approaches, including threshold segmentation, edge-based segmentation, watershed segmentation, neural networks for segmentation, and many others. Humans do the job of image segmentation naturally and unconsciously. On the other hand, it is not very easy to teach a computer to intelligently recognize different objects, so several algorithms have been developed to segment images. We have used U-Net architecture for our analysis and project development.

2. Materials & Methods

2.1 Convolution Neural Networks

Neural networks, which were initially proposed in 1944, have, however, received little attention during the subsequent 70 years. They now have a fresh lease on existence thanks to the advent of artificial intelligence. Recently, the term "Deep Learning," a new name for neural networks, has gained popularity. Some of the most cutting-edge AI systems now in use are built on deep learning. A neural network is composed of three layers: the input layer, the hidden layer, and the output layer. Each of these layers consists of a number of nodes that link to one another and each of them has a weight and bias value associated with it. The activation function, which receives the data output by the node, in turn outputs the likelihood that the values will be, produces whether the values will be passed to the next layer or not. Convolution Neural Networks (CNN) are a specific class of neural network that are frequently used to address problems based on input from images or videos. In comparison to other image classification techniques, these networks require comparatively less pre-processing, which implies that after training for a sufficient amount of time, the network can modify its filter settings to be able to recognize various objects or patterns. Convolution layer, Pooling layer, and Fully Connected layer make up the majority of CNNs' layers. AlexNet, VGGNet, GoogLeNet, ResNet, MobileNet, and Dense Net are some of CNN's most well-liked architectures.

2.2 Image Segmentation

Picture segmentation is the process of splitting a picture into separate segments according to predetermined criteria. When a segmentation algorithm is given a picture to work with, it creates a collection of areas (or segments) that may be seen as:

- A group of contours
- A color or grayscale mask where each segment is given a different color or grayscale value to help identify it.

2.2.1 Semantic Segmentation: In semantic segmentation, each pixel in the picture is given a label, such as "car," "building," "person," etc. The outcome of semantic segmentation is depicted in Figure 2. In Figure 2, the pixels that indicate humans are red, the pixels that represent grass are light green, the pixels that represent trees are dark green, and the pixels that represent the sky are blue. If a pixel is red, we can quickly determine if it belongs to the "person" class, but there is no way to determine if the two red-colored mask pixels represent a single person or two distinct individuals.

Figure 1. Image

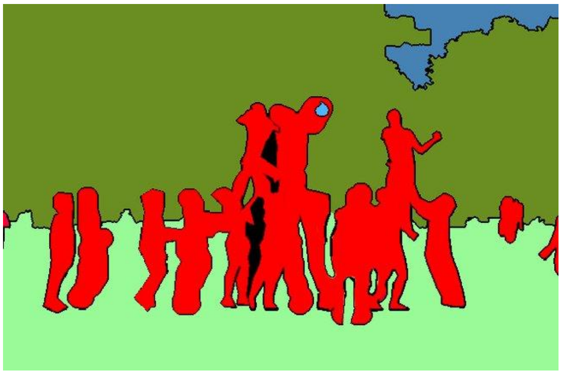

Figure 2. Semantic Segmentation

2.2.2 Instance Segmentation: The concept of instance segmentation is quite similar to that of object detection. The result in this instance, as opposed to item Detection, is a mask that contains the item as well as the bounding box coordinates. Unlike Semantic Segmentation, we are simply concerned with locating the boundaries of particular objects and do not need to identify every pixel in the image. A Mask R-CNN instance segmentation architecture's output is shown in Fig. 3. We can tell each person apart because we can distinguish between their masks.

Figure 3. Instance Segmentation

2.3 U-Net Architecture

Olag Ronneberger et al. introduced the U-Net architecture to aid in the segmentation of biomedical images. Encoder and decoder were the major components of the newly presented architecture. The focus of the encoder is the Max Pooling operation, which is followed by Convolution Layers. It is employed to extract the image's features. Transposed Convolution Layers are used by the second part decoder to upscale the image. Concatenation layers are used in between which help in retaining the object localization information. It is a Fully Connected Layers Network.

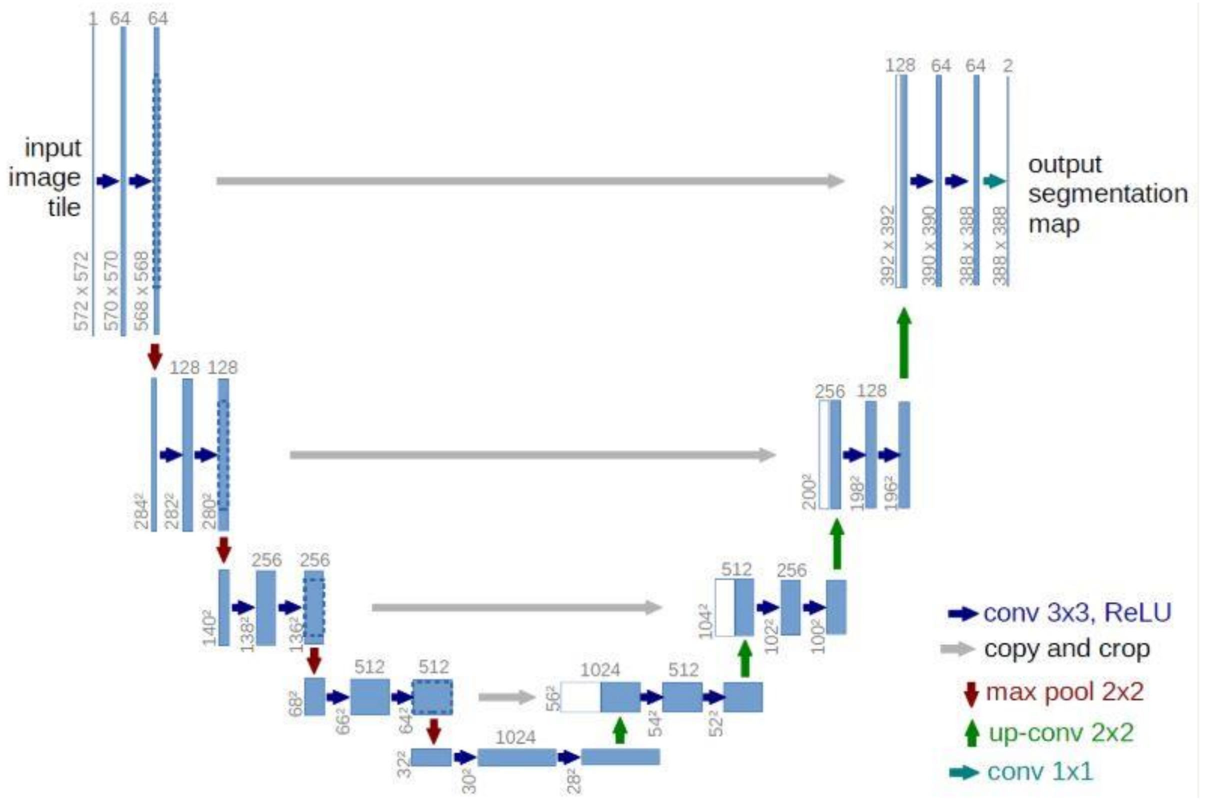

Figure 4. U-Net Architecture

3 Results & Discussions

3.1 Metrics and Loss

A. IoU Score

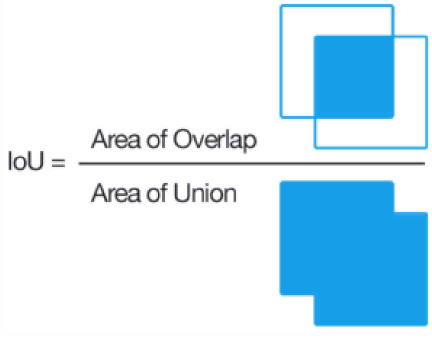

Figure 5. IoU Score

Jaccard index is another name for IoU. IoU is defined as the area of union between the ground truth and expected segmentation divided by the area of overlap between the two. The metrics range from 0 to 1, with 0 denoting no overlap and 1 denoting complete overlap between the anticipated segmentation and the ground truth. For better results we have to maximize IoU. IOU or J(A, B) = A ∩ B A ∪ B OR TP TP + FP + FN IoU los OR jaccard loss = 1 - IoU.

B. Dice Coefficient

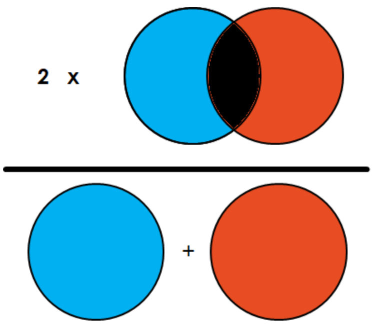

Figure 6. Dice coefficient

Dice coefficient is also termed as f1 score. The dice coefficient is calculated by dividing the area of overlap by the sum of the pixels in both photos. Dice coefficient (F1 score) = 2 intersection, intersection + union, OR 1 precision, 1 recall, dice loss, where dice loss is equal to 1 - Dice coefficient.

C. Cross Entropy

A measurement of the variance between two probability distributions is called cross entropy.

$$\mathrm{CE} = -\sum_{i=1}^{n} y_i \log(p_i) \tag{1}$$

D. Binary Cross Entropy

In cross entropy, n=2 for binary cross entropy. The discrepancy between projected probability and corrected probability is penalized by the log value differently depending on how little or huge the difference is. For logs from 0 to 1, log values are negative. To make up for this negative value, we utilize the negative average of the values.

$$\mathrm{bce} = \frac{1}{N} \sum_{i=1}^{n} -(y_i \log(p_i) + (1 - y_i) \log(1 - p_i)) \tag{2}$$

E. Focal Loss Focal

Cross entropy loss has been enhanced to create focal loss. It increases the loss for difficult to categorize classes while decreasing the loss for classes that are well-classified. In summary, Focal loss turns model attention towards the difficult to classify class.

$$\mathrm{CE} = -\log(p_t) \tag{3}$$

$$\mathrm{FL} = -(1 - p_t)^{\gamma} \log(p_t) \tag{4}$$

If $\gamma = 0$FL is same as CE.

F. Combined Loss

Bce dice loss = binary cross entropy + dice loss

Bce jaccard loss = binary cross entropy + Jaccard loss

Cce dice loss = categorical cross entropy + dice loss

Cce Jaccard loss = categorical cross entropy + Jaccard loss

Binary focal dice loss = binary focal loss + dice loss

Binary focal Jaccard loss = binary focal loss + Jaccard loss

Categorical focal dice loss = categorical focal loss + dice loss

Categorical focal Jaccard loss = categorical focal loss + Jaccard loss

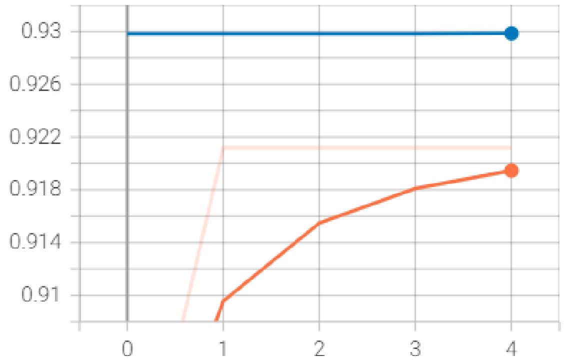

Figure 7. Epoch Accuracy

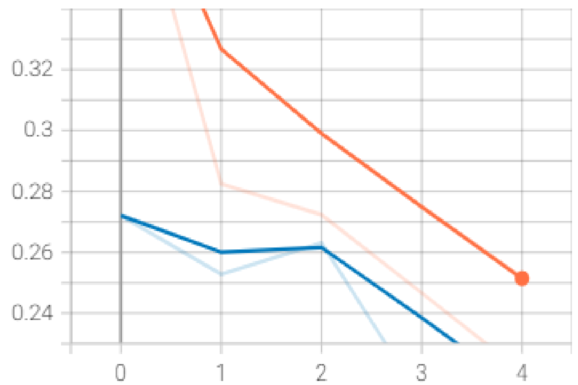

Figure 8. Epoch Loss

4. Conclusion

The dataset used for training/testing is taken from Open-Source. We tested a number of cutting-edge architectures as the foundation of our U-net model, and InceptionResNet-v2[3] produced the best outcomes. 50 epochs were used to train the model. A graph of model accuracy with epochs is shown in Fig. 7. A graph of model loss with epochs is shown in Fig. 8. We were able to achieve 98% accuracy on training data and 96% accuracy on testing data.

Conflict of Interest

The authors affirm that they have no conflict of interests with regard to this research work. They have received no financial support or funding that could have influenced the design, execution, or interpretation of the study results. They also have no personal or professional relationships that could have affected their research in any way. The research findings and conclusions are completely based on the examination of the data gathered, and all of the authors have made objective and impartial contributions to this study.

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