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Deep Learning Advancements in Breast Cancer Lesion Detection Using U-Net Methodologies

Dr. Vijaya Chandra Jadala

Associate Professor, Department of CSE, Koneru Lakshmaiah Eucation Foundation, Vaddeswaram, Guntur, 522302-India. Email: vijayachandra.phd@gmail.com

Abstract.

The Breast cancer remains a critical global health concern, involves advanced diagnostic tools for early detection of breast cancer and advanced scanning methodologies helps doctors, medical practioners for easy diagnotistics and to improve patient health. This research explores the application of deep learning methodologies, specifically focusing on the U-Net architecture, to enhance the accuracy and efficiency of breast cancer lesion detection. The U-Net, renowned for its success in medical image segmentation, is employed to analyze mammographic images with the aim of identifying and marking an outline for breast cancer lesions. The Experiment is done based on the BUSI (**B**reast **U**ltra **S**ound **I**mages) dataset which is adopted from kaggle, the dataset consists of three different categories based on the level of lesion percentage. Our study demonstrates the effectiveness of U-Net in accurately detecting and segmenting breast cancer lesions from complex mammographic data. The proposed methodology exhibits promising results, showcasing its potential as a robust tool for automated breast cancer diagnosis. Experiment majorly include model training on diverse datasets, validation using established benchmarks, and comparative analyses with help of graphical analysis is provided against traditional methods.

Keywords: Deep learning, U-Net, Dataset, Breast Cancer.

1. Introduction

Breast cancer is a widespread and potentially life-threatening disease affecting millions of women globally. Early detection plays a pivotal role in improving survival rates and treatment outcomes. Medical imaging, particularly mammography, has been instrumental in the early diagnosis of breast cancer, allowing clinicians to identify abnormalities such as

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tumors or masses. However, the interpretation of mammograms can be a complex and time-consuming task, necessitating advanced computational tools to aid in the diagnostic process.

In recent years, deep learning approaches have demonstrated remarkable success in various image analysis tasks. One such architecture, the U-Net, originally designed for biomedical image segmentation, has shown promise in accurately delineating structures within medical images. Its unique architecture, featuring a contracting and expansive path with skip connections, enables the capturing of both global and local features, making it particularly suitable for tasks like breast cancer detection. The motivation behind this research lies in the potential of the U-Net architecture to improve the efficiency and accuracy of breast cancer detection. By leveraging the capabilities of deep learning, we aim to develop a robust model that can assist radiologists in identifying and classifying suspicious regions in mammographic images. This augmentation of the diagnostic process could lead to earlier interventions, improved patient outcomes, and a reduction in false positives and negatives [1].

The objective, include the implementation and evaluation of a U-Net-based model for breast cancer detection using a diverse dataset of mammographic images. We seek to assess the model's performance in terms of sensitivity, specificity, and overall accuracy, comparing it with traditional methods and existing deep learning architectures.

2. U-Net Deep Learning Model

The architecture is characterized by its U-shaped structure, which consists of a contracting path and an expansive path. The contracting path captures context and reduces spatial resolution, while the expansive path enables precise localization. Skip connections between corresponding layers of the contracting and expansive paths facilitate the flow of high-resolution information during the up-sampling process. The U-Net architecture is a convolution neural network (CNN) designed for image segmentation tasks. It was originally developed for biomedical image segmentation, including applications like cell and tissue segmentation in microscopy images [2].

Experimental purpose we used Google co-lab for implementation of deep learning methodologies, importing the **BUSI** data set by using the following snippet code.

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```
from google.colab import drive
drive.mount('/content/gdrive')

    Mounted at /content/gdrive


!unzip gdrive/My\ Drive/Dataset_BUSI_with_GT.zip

      inflating: Dataset_BUSI_with_GT/normal/normal (73).png
      inflating: Dataset_BUSI_with_GT/normal/normal (73)_mask.png
      inflating: Dataset_BUSI_with_GT/normal/normal (74).png
      inflating: Dataset_BUSI_with_GT/normal/normal (74)_mask.png
      inflating: Dataset_BUSI_with_GT/normal/normal (75).png
      inflating: Dataset_BUSI_with_GT/normal/normal (75)_mask.png
      inflating: Dataset_BUSI_with_GT/normal/normal (76).png
      inflating: Dataset_BUSI_with_GT/normal/normal (76)_mask.png
```

Figure 1 Snippet for calling BUSI – Data Set – for Deep Learning Implementation.

Implementing a U-Net model for image segmentation often involves using libraries such as NumPy, pandas (for data manipulation), and TensorFlow (or other deep learning frameworks like PyTorch). U-Net or similar architectures are commonly used for semantic segmentation tasks. This involves classifying each pixel in an image, assigning it to a particular class or category. The U-Net model would be trained on this dataset to learn the patterns and features associated with the segmented areas. Image segmentation techniques can be applied to Images in BUSI data set [3].

```
The directory structure
dataset/
├── images/
│   ├── image1.jpg
│   ├── image2.jpg
│   └── ...
└── masks/
    ├── mask1.jpg
    ├── mask2.jpg
    └── ...
```

Figure 2 BUSI – Data set – Directory Structure after Classification.

3. Data set

The different Datasets available for Breast cancer detection related to medical image processing are as follows, The INbreast dataset was created to support research efforts in developing and evaluating algorithms for the detection and characterization of breast lesions. It includes images that are annotated with ground truth information, providing a basis for the training and evaluation of machine learning and deep learning models. Breast Cancer

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Pathology Diagnostic dataset, is a publicly available dataset focused on breast cancer pathology. The dataset is designed to facilitate research in the development and evaluation of machine learning and computer vision algorithms for breast cancer diagnosis. Kaggle is a platform where you can find numerous datasets related to the breast cancer. Kaggle kernels also provide cloud-based computational resources [4].

The SPIE-AAPM-NCI Breast Pathology dataset is a collection of breast pathology images used in the SPIE-AAPM-NCI Breast Pathology (BRP) Challenge, organized by SPIE (International Society for Optics and Photonics), AAPM (American Association of Physicists in Medicine), and NCI (National Cancer Institute). This challenge aimed to encourage the development of computer-aided diagnostic (CAD) algorithms for breast pathology.

After observing different datasets we selected the BUSI dataset, The BUSI dataset plays a crucial role in the validation process. Comprising 780 images, each with an average size of 500 × 500 pixels, the dataset encompasses three distinct categories: normal (133 images), malignant (210 images), and benign (487 images), To facilitate the training and testing phases, we partitioned the entire dataset into a 50:50 ratio [5].

Subsequently, the distribution of training images for each class is as follows: normal (56 images), malignant (105 images), and benign (243 images). Recognizing that this dataset alone may not be sufficient to effectively train a deep learning model, we incorporate a data augmentation step. Leveraging operations such as horizontal flip, vertical flip, and a 90-degree rotation, these augmentations are applied to the original ultrasound images, introducing diversity to the dataset. These operations are iteratively performed until the number of images in each class reaches 4000. Post-augmentation, the dataset comprises a total of 12,000 images.

The dataset was associated with a challenge where participants were invited to develop algorithms for specific tasks related to breast pathology, such as the detection and classification of breast cancer [6].

Table 1 Number of Datasets relate to Breast Cancer

S.No	Data Set	Description
1	Breast Cancer Wisconsin	This dataset contains features computed from a digitized image of a fine needle aspirate (FNA) of a breast mass. It is binary model of malignant or benign.

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2	Mammographic Mass	This dataset includes mammographic images and features extracted from them. The task is to predict whether a mammogram mass is benign or malignant.
3	INbreast	The INbreast dataset includes mammography and breast ultrasound images. It is designed for research in breast cancer detection and diagnosis.
4	SPIE-AAPM-NCI Breast Pathology	The dataset comprises breast pathology images, specifically high-resolution digital pathology images of breast tissue samples.

4. U-Net Architecture

The U-Net architecture is a convolution neural network (CNN) architecture designed for semantic segmentation tasks, particularly in biomedical image analysis. It was introduced by Olaf Ronneberger, Philipp Fischer, and Thomas Brox in 2015 and has since become popular in various image segmentation applications. The U-Net architecture is characterized by its U-shaped structure, which resembles an encoder-decoder network. It is particularly effective for tasks where precise localization of object boundaries is crucial, such as in medical image segmentation. The U-Net architecture has been successfully applied to various segmentation tasks for medical imaging, It is known for its ability to handle small datasets effectively and produce accurate segmentation results.

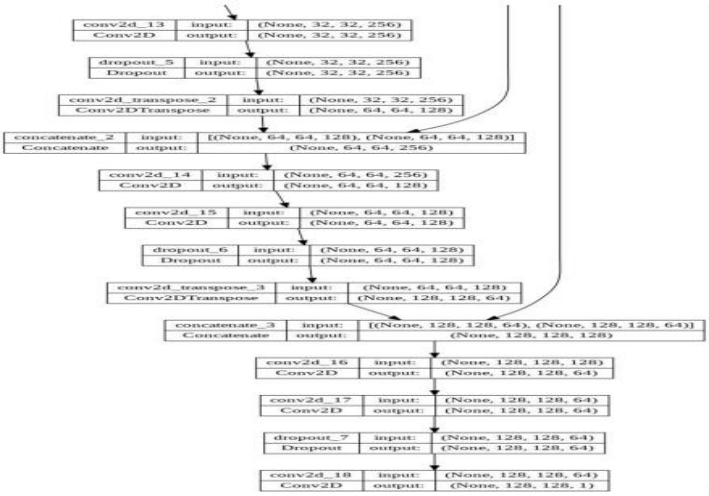

Figure 3 U-Net Architecture – Deep Learning Implementation

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The U-Net architecture is a convolutional neural network (CNN) architecture designed for semantic segmentation tasks, particularly in biomedical image analysis. It was introduced by Olaf Ronneberger, Philipp Fischer, and Thomas Brox in 2015 and has since become popular in various image segmentation applications.

The U-Net architecture is characterized by its U-shaped structure, which resembles an encoder-decoder network. It is particularly effective for tasks where precise localization of object boundaries is crucial, such as in medical image segmentation.

Here's a high-level overview of the U-Net architecture consists of Encoder Path which is left side of the U-Net is responsible for capturing context and extracting features from the input image. Next is Bottleneck, At the bottom of the U shape, there is a bottleneck layer that captures the most compact representation of the input. Later Decoder Path is the right side of the U-Net is the decoder path, responsible for upsampling and refining the features to produce the segmentation mask. Skip connections connect the encoder and decoder paths at multiple levels. These connections allow the decoder to access feature maps at different scales, helping to recover fine details. The final layer of the U-Net typically consists of a 1x1 convolutional layer followed by a softmax activation function in binary segmentation tasks or a softmax-like activation for multi-class segmentation.

The U-Net architecture has been successfully applied to various segmentation tasks beyond medical imaging, such as satellite image segmentation, road segmentation, and more. It is known for its ability to handle small datasets effectively and produce accurate segmentation results.

5. Results and Discussion

The original image is the raw or unprocessed medical image that is acquired through imaging modalities such as X-ray, mammography, ultrasound, or magnetic resonance imaging (MRI).

In the case of breast cancer detection, the original image typically represents the anatomical structure of the breast as captured by the imaging device.

The masked image is derived from the original image and represents a binary or grayscale image where certain regions of interest are highlighted or "masked". The mask is often created manually or through automated segmentation algorithms to highlight specific

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structures or abnormalities in the original image. In the context of breast cancer, these structures may include tumors, lesions, or other areas of interest.

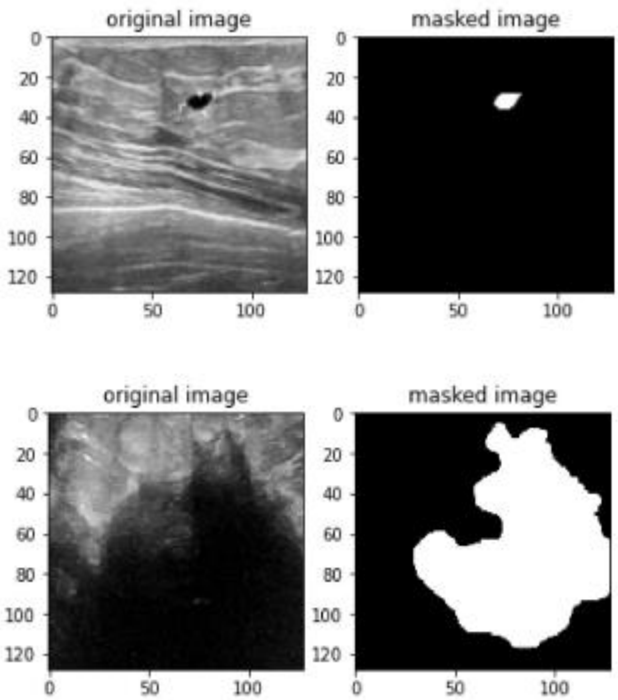

Figure 4 U-Net Implementation on Original Image of BUSI dataset to achieve Masked Image

The masked image helps focus the analysis on regions that are critical for diagnosis, aiding in the detection and characterization of potential abnormalities. U-Net, being a semantic segmentation model is well-suited for tasks involving the creation of detailed masks for specific structures in medical images.

6. Conclusions

The Model accuracy is a crucial aspect of model evaluation, but it should be considered alongside other metrics and visualizations to gain a comprehensive understanding of the model's performance. Overemphasis on accuracy alone may lead to misinterpretations, especially in imbalanced datasets or when specific requirements demand a focus on precision, recall, or other metrics. The training and testing graphical representation is used to visualize the training and validation accuracy across epochs using a simple matplotlib plot.

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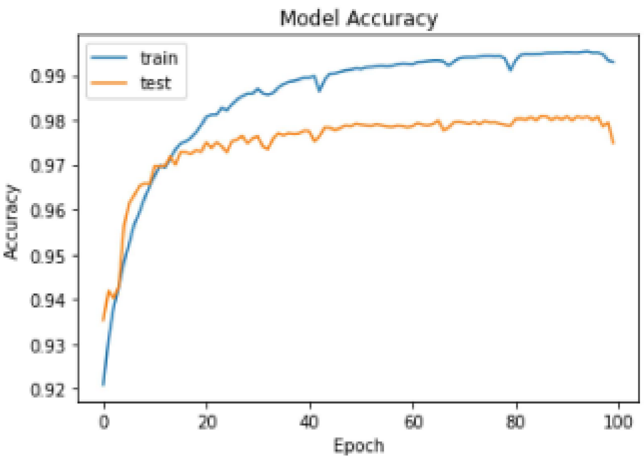

Training and testing a deep learning model for breast cancer detection involves several steps, including data preparation, model architecture design, training, and evaluation. For Model architecture design we used U-Net Convolution Neural Network Model. Finally we receive the output and result analysis in the form of Model Accuracy.

Experiment with hyper-parameters and architecture based on the characteristics of your dataset.

If necessary, fine-tune the model based on the evaluation results. Adjust hyper-parameters or consider using transfer learning. Train the U-Net model using the training dataset. Monitor training metrics such as loss and accuracy. Finally Evaluate the model on the testing dataset to assess its performance and Monitor for over-fitting by observing the difference between training and validation performance. The fit method is used to train the model. The training history (history) object contains information about training metrics over epochs. After training, you can access the test accuracy using **model.evaluate** on the test set.

Adjust the code based on the specifics of your dataset, U-Net architecture, and requirements. Monitoring accuracy across epochs helps in understanding the training progress and potential issues with overfitting or underfitting.

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