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Implementation of U-Net Architecture for Medical Image Segmentation in Breast Cancer Detection Using Ultrasound Dataset

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Abstract

Medical image segmentation is one of the important methods in the field of image analysis to support automatic diagnosis of diseases. In this study, the application of U-Net architecture in segmenting breast cancer ultrasound images is proposed. The dataset used is a collection of ultrasound images with three categories: benign, malignant, and normal. Preprocessing is done by reducing the image size and removing classes without annotations. The U-Net architecture was built from scratch and trained using binary crossentropy loss function and accuracy metrics. Model evaluation is performed based on Mean Intersection over Union (IoU), Precision, Recall, and F1-Score metrics. The test results show that the model is able to perform tumor segmentation quite accurately on low-resolution medical images. This research shows that U-Net can be an efficient solution to assist ultrasound image-based breast cancer detection.

Keywords : *medical image segmentation, U-net, breast cancer, deep learning, ultrasound imaging, model evaluation*

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Introduction

Breast cancer is one of the leading causes of death in women worldwide. Early detection has a crucial role in increasing the chances of a patient's recovery. Ultrasound imaging (ultrasound) is one of the methods that is often used because of its non-invasive, inexpensive, and safe nature. However, manual interpretation of ultrasound images often relies on radiological expertise which has the potential to give rise to subjective variations. In recent years, the development of deep learning, particularly the U-Net model, provides innovative solutions to challenges in medical image segmentation. U-Net is a convolutional neural network (CNN) architecture designed specifically for image segmentation tasks, and has proven to be effective in detecting and separating critical tumor-like areas in various types of medical imaging.

This study aims to apply and evaluate the U-Net model in segmenting tumor areas in breast ultrasound images using the BUSI. By utilizing evaluation metrics such as IoU, Precision, Recall, and F1 Score, this study is expected to demonstrate the effectiveness of U-Net in supporting automatic and accurate breast cancer diagnosis. Various studies have proven the effectiveness of the U-Net algorithm in segmenting medical images. Ronneberger et al. (2015) first introduced U-Net for microscopic cell segmentation, which was later widely adopted in various medical domains.

A study by Arya Shah et al. (2023) showed that the application of U-Net to breast ultrasound images was able to improve the accuracy of tumor segmentation with a multi-mask approach. In

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addition, research by Zhang et al. (2024) added an attention mechanism to increase focus on tumor areas, which strengthens the basic architecture of U-Net. Other references such as DBU-Net (Kumar, 2023) and LightBTSeg (Li et al., 2024) developed U-Net variants to overcome the limitations of resolution and annotation data counts. This shows that U-Net and its derivatives are a flexible approach that can be optimized for a wide range of medical data conditions. This study used the conventional U-Net approach as a baseline to evaluate its performance on the BUSI dataset, which contains ultrasound images of patients with benign, malignant, and normal conditions. By eliminating the normal class (without mask), the model is focused on detecting and segmenting the two main types of tumors.

This study examines the influence of Kiyai Haji Ahmad Dahlan (1868–1923) on the Islamic reform movement in Indonesia and the impact of his ideas on modern movements and thought. The study is situated within the context of religious reform and purification promoted by the Muhammadiyah Islamic organization, which he founded on November 18, 1912. This research aims to uncover the philosophical foundations and strategic principles of struggle articulated in the reform movement he pioneered as a forerunner of modern awareness and revival, to analyze the transformation of puritan Islamic thought within the Indonesian context, and to evaluate the relevance of Ahmad Dahlan's method of *ijtihad* in responding to the challenges of modernity and contemporary religious pluralism.

The objective of this study is to reveal the philosophy and guiding principles of struggle embedded in the reform movement he initiated as a pioneer of modern consciousness and revival. The research method is descriptive-historical, based on a qualitative review using scientific and empirical approaches. The findings indicate that Ahmad Dahlan's thought has exerted significant influence and impact on modern Islamic aspirations advanced by Muhammadiyah through its extensive network of activists and preachers. This influence has contributed to the development of rationalist tendencies and heightened awareness emerging from the *madhhab* tradition and his puritan perspective. The values of *ijtihad* and this line of thought were further developed within his purification movement as part of Muhammadiyah's cosmopolitan vision to strengthen Salafi da'wah networks and enhance organizational capacity, positioning it as one of the largest and most well-organized Islamic movements in the world.

Method

1. Research Design

This study uses an experimental quantitative approach with a deep learning-based image processing method for medical segmentation tasks. The deep learning model used is the U-Net architecture, which is specifically designed for two-dimensional image segmentation. This study focused on segmentation of breast tumors from ultrasound images with the aim of separating cancerous areas (benign and malignant) from normal tissue.

2. Dataset

The dataset used in this study is *the Breast Ultrasound Images Dataset (BUSI),* developed by Mohamed and Hazem. This dataset consists of 780 grayscale images from breast ultrasound scans divided into three classes, namely benign (437 images), malignant (210 images), and normal (133 images). However, normal classes are excluded from the training process because they are not accompanied by mask annotations that can be used in segmentation. Each image in the dataset has a ground truth pair in the form of a binary mask that shows the location of the lesion or tumor. For the processing needs and consistency of the model's input dimensions, all images and masks are resized to 128 × 128 pixels and normalized in the range of 0–1.

3. Model Architecture

The segmentation model used is U-Net, a convolutional neural network (CNN) architecture consisting of two main components:

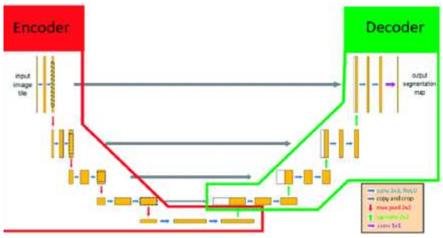

Figure 1. encoder and encoder components on the U-Net Architecture

a. An encoder *(contraction* path) that is in charge of extracting special features through the max poll convolution layer.
b. Decoder *(Expanding path)* which is in charge of reconstructing segmentation maps using up sampling and concanetation with the features of Encoder

The U-Net architecture used consists of four encoder blocks and four decoder blocks, with one bottleneck in the middle. Each convolutional block uses a 3×3 size filter and a ReLU activation function, and the output layer uses sigmoid activation to generate a binary mask.

Preprocessing Data

Preprocessing steps include:

a. Read images and masks using OpenCV
b. Resize image to 128×128 pixels
c. Conversion to grayscale
d. Normalization of pixel values
e. Reshape dimension expansion to fit model input format (128, 128, 1)
f. The division of data into training data (90%) and test data (10%) uses the train_test_split function.

Model Training Procedure

The U-Net model is trained using the Binary Crossentropy loss function, the Adam optimizer, and the accuracy metric. The training process is carried out for 100 epoches with the default batch size. Validation is carried out on the test data periodically to avoid overfitting. During training, the data is not subject to augmentation to maintain the original distribution of the dataset.

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Evaluation and Visualization of Results

The trained model was evaluated using several segmentation evaluation metrics as follows:

a. *Mean Intersection over Union (IoU)*
b. Accuracy
c. Recall
d. F1 Score

The prediction results of the model are displayed in visual form, by comparing the original image, the ground truth mask, and the model's prediction results. These results are visualized for each category of tumors.

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Implementation and Testing Environment

The entire implementation is carried out using the Python programming language on the Google Colab platform. The libraries used include:

a. *TensorFlow* and *Keras* for deep learning models,
b. *OpenCV* for image processing.
c. *Numpy* and Matplotlib for analysis and visualization.

The specification of the training environment includes:

a. T4 GPU *(from the colab runtime).*
b. Ram 12 *(Shared).*
c. Python 3.10
d. Tensoreflow 2.12

Results and Discussion

The U-Net model was trained for 100 epochs using breast cancer imaging data from the BUSI. The training process shows a stable convergence on accuracy and loss metrics, both in training data and validation. The accuracy graph shows a consistent increase with each epoch, while the value of the loss tends to decrease gradually until it is close to stable. A visualization of the training results can be seen in the following Figure 1.2:

1. Segmentation Results

The model was tested on test data comprising 10% of the total dataset that had been processed. The segmentation results showed that U-Net was able to identify tumor areas well, including tumor shape, position, and boundaries, in both benign and malignant images.

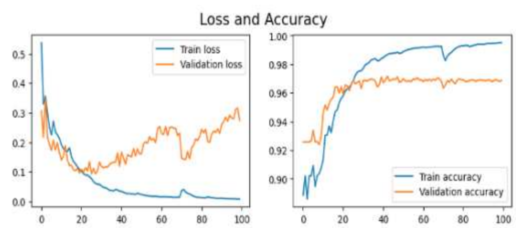
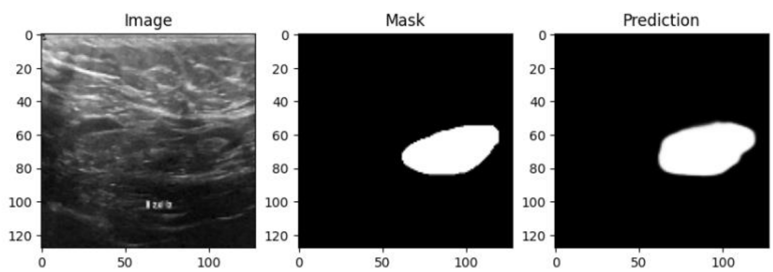


Figure 2. visualization of lost results and training accuracy of the Unet model

An example of the prediction results is presented in Figure 1.3, which shows the input image, ground truth mask, and model prediction results:



These results show that the model is able to provide results that visually resemble the original annotated mask.

2. Quantitative Evaluation

The model was evaluated using segmentation evaluation metrics, with the following results:

a. Mean IoU 0.80
b. Accuracy Score 0.77
c. Recall Score 0.80
d. F1 Score 0.78

These values show that the model has a high and balanced segmentation performance. An F1 Score value close to 1 indicates that the model is not only accurate in detecting tumor areas, but also minimal in false positive and false negative errors.

Discussion

U-Net's success in segmenting tumors in breast ultrasound images is supported by architectural characteristics that are able to retain important spatial information through a concatenation mechanism between the encoder and decoder layers. In addition, the BUSI dataset that has a good annotation structure is also a supporting factor in the effectiveness of the model training. However, there are several challenges that still need to be considered, including:

a. Variations in texture and intensity in the image (ultrasound) that can interfere with segmentation.
b. The relatively small size of the dataset can limit the model's generalization to real-world data.
c. An imbalance in the amount of data between the benign and malignant classes that can affect performance.

This research can consider the use of augmented data, *U-Net architecture* with attention mechanisms, and ensemble techniques to improve the accuracy and robustness of the model against noise and data variation.

Conclusion

This study shows that the U-Net architecture is effectively used for tumor segmentation tasks in breast ultrasound (ultrasound) images. Using the systematically processed BUSI dataset, the model managed to achieve satisfactory evaluation performance, namely: Mean IoU 0.80, Accuracy Score 0.77, Recall Score 0.80, F1 Score 0.78 These results prove that U-Net is able to produce accurate and comparable segmentation of tumor areas with ground truth annotations from medical data. The use of this method can support the process of automatic early diagnosis of breast cancer, while reducing reliance on manual interpretation by radiologists. In general, U-Net is proven to be a reliable deep learning solution in detecting and separating important areas of medical imagery, particularly in the breast cancer domain.

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