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Breast Cancer detection using Transfer Learning

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ABSTRACT: Globally, breast cancer continues to be the most prevalent and severe type of cancer among women. For better survival rates and efficient treatment, early and precise detection is essential. In this work, we introduce a deep learning-based method that uses the Resnet50 model and Transfer Learning to detect and provides the classification score of breast cancer ultrasound images. To enhance image efficiency and model generalization, the suggested system uses sophisticated pre-processing methods such data augmentation, normalization, and noise reduction. To speed up training and increase accuracy, a pre-trained model is adjusted using domain-specific ultrasound image data. Experiments on the Breast Ultrasound Image Dataset (BUSI) show encouraging results; the classification model maintains low loss values while attaining an accuracy of 95.33% and validation accuracy of 90.15%. With time, the segmentation component's detection ability improves when it is tuned using a dice loss function. When utilized in a desktop application, this integrated technique greatly improves automated breast cancer diagnostics speed and reliability. The findings highlight Transfer Learning's potential for early breast cancer diagnosis in practical clinical settings.

Keywords: Breast cancer detection, Transfer Learning, ResNet50 Model, Ultrasound Imaging, Image Segmentation.

1. Introduction

Breast cancer remains one of the most serious ailments affecting women today. The likelihood of recovery is significantly increased when it is discovered early. Transfer learning has drawn interest recently due to its accuracy in processing and categorising medical images. In this experiment, ultrasound images are used to identify breast cancer using transfer learning, specifically transfer learning. We can utilise transfer learning to adapt models that were previously trained on large datasets to our specific objective while utilizing fewer resources. To find the optimal model for this challenge, we employed three distinct pre-trained convolutional neural network (CNN) models: InceptionV3, Efficient-Net, and ResNet50. Our dataset of images of breast tissue was used to refine each model. We found that several models had trouble correctly classifying the photos during testing, but that ResNet50 was better at identifying the patterns required for precise findings. We have taken a number of crucial actions. To meet each model's input size requirements, images were first pre-processed and contracted. To increase the diversity and quality of training samples, data augmentation approaches were applied. Following data preparation, conventional performance criteria were used to train and assess the models. We were able to comprehend each model's advantages and disadvantages. According to our research, selecting the appropriate architecture is essential to getting good results when classifying medical images. The ResNet50 model, with its deeper structure and skip connections, was able to distinguish detailed elem ents in the images which improved its prediction accuracy. This illustrates the manner in which deep learning may be used successfully in medical environments. This study aims to demonstrate how artificial intelligence could aid oncologists diagnose as well as to developing a functioning categorization model. This kind of dependable method can help medical experts, decrease human mistake, and expedite the diagnostic procedure. This can be particularly useful in places with limited access to skilled pathologists. This project shows that transfer learning is a useful and effective method for detecting breast cancer, which could result in improved treatment outcomes.

2. Related Works

Sheeba Armoogum and et.al, has summarized in the paper "The prevalence of breast cancer among women has increased, highlighting the importance of early diagnosis and categorisation for illness prevention. The prediction process is made easier by integrating machine learning, which reduces the time and expense of disease diagnosis. Similarly, the goal of this study was to use the BUSI dataset from Kaggle to build a VGG-16 CNN model with Transfer Learning. The dataset was subjected to necessary preprocessing steps prior to training, such as contrast enhancement, denoising, and image scaling. The most effective arrangement produced accuracy, loss, validation accuracy, and validation loss of 0.9015, 0.2641, 0.9012, and 0.3115, respectively, after a variety of test-size ratios were used during training. After training, the model was downloaded locally and added to our desktop application."

Fahad Ahmed and et.al, has conveyed that "The ResNet50, ConvNextTiny, and Inception-ResNet models perform comparably to the most advanced multi-instance learning (MIL) techniques currently in use for the classification of gigapixel pictures used in breast cancer histopathology. We used three distinct methods to conduct this study. Using the default BRACS dataset splits, we tested the first strategy. The ResNet50 model outperformed SOTA models in our test results, attaining a 65% F1-score. We divided the dataset into bespoke train- val-test divides and up-sampled it to 1000 samples per class for our second technique. The EfficientNet demonstrated the best classification performance in our test results, obtaining a 77% F1-score and 77% sensitivity. Our third strategy involved randomly dividing the dataset into train-val-test customsplits (90%-7%-3%) and up-sampling the dataset to 2000 samples per class. With a 96.2% F1-score and 96.2% sensitivity, the RestNet50 model provided the greatest classification performance in our test results utilising this data split."

3. Proposed Work

This suggested work focusses on image acquisition, which is the step in which the system begins by collecting data from ultrasound pictures of the breast, including normal, benign, and cancerous stages, which is then used for image segmentation. A critical stage is model annotation, which involves employing ground truth masks to precisely detect malignant spots on images. Artificial intelligence (AI) has advanced significantly since the inception of deep learning. In computer vision, ResNet-50 has been one of the popular and effective deep neural networks. It is capable of producing cutting-edge outcomes in a variety of image-related works, along with object recognition, image classification, and image segmentation.

ResNet is an acronym for residual network, and it refers to the residual blocks that comprise the network's architecture. The ResNet model is based on a deep residual learning framework that allows the construction of incredibly deep networks with hundreds of layers. ResNet-50 consists of 50 layers divided into five blocks, each containing a number of residual blocks. The residual blocks preserve information from preceding layers, allowing the network to learn more accurate representations of the input data.

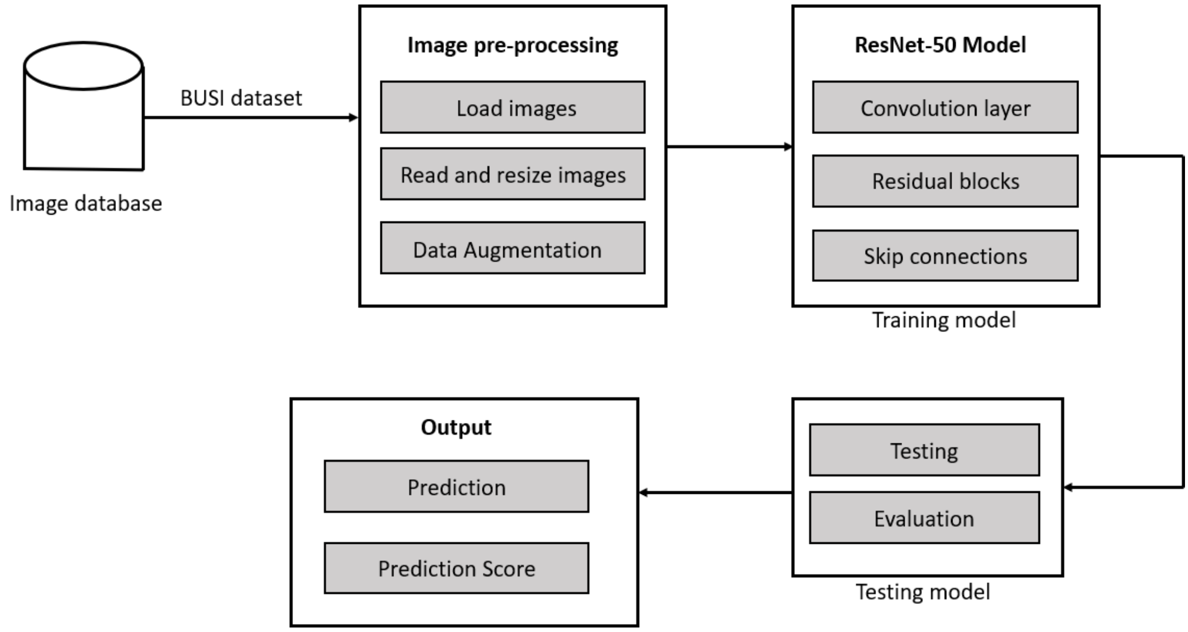

Figure 1: *Data Flow diagram of Proposed Work*

Figure 1 depicts the flow diagram for the proposed system, which uses the ResNet-50 architecture. Here data that takes the BUSI images, is gathered in a database, and is used as input for image pre-processing. In image pre-processing, the images are loaded, read and resized based on the requirements. Image pre-processing additionally plays extremely crucial in terms of data augmentation which is later used in training the model. ResNet-50 model consists of residual blocks, convolution layers and skip connections which is used for training. Later on, images are tested and evaluated. Output consists prediction of type of ultrasound image and its prediction score.

3.1 Image Pre-processing

In order for the deep learning model to accurately forecast ultrasound pictures, image preprocessing is an essential step. The BUSI dataset's raw images for our research frequently differ in size, resolution, and quality, which, if not normalized, might have an adverse impact on model performance. In order to match the input dimensions required by the improved ResNet50 model, each image is first downsized to 128×128 pixels. This scaling preserves crucial structural information while ensuring computational efficiency. TensorFlow models are usually trained on RGB input, hence OpenCV is used to convert the BGR images to RGB color representation. To normalise the pixel values, they are scaled to a range of 0 to 1. As a means to promote convergence and accelerate the training process, each pixel value is divided by 255.0. To convert the image into a 4D tensor (1, 128, 128, 3), which can be given via the convolutional neural network's output, an extra batch dimension is added at the end. By standardizing the dataset images and improving the model's ability to develop discriminative features across the three categories of benign, malignant, and normal, these preparation methods raise the classification accuracy.

3.2 ResNet50 Architecture

ResNet50 is a 50-layer deep convolutional neural network that uses residual connections to solve the vanishing gradient issue in very deep networks. We employ a modified version of ResNet50 as a characteristic generator for transfer learning in our breast cancer detection project. The final classification layer has been designed to predict three classes: normal, malignant, and benign.

3.2.1 Convolutional Layer

The first layer of the network applies convolution to the input image, which is a convolutional layer. A max-pooling layer that down samples the convolutional layer's output comes next. A sequence of leftover blocks is subsequently applied to the max-pooling layer's output.

3.2.2 Residual Blocks

A rectified linear unit (ReLU) activation function and a batch normalization layer come after each of the two convolutional layers that make up each residual block. After adding the result of the second convolutional layer, the residual block's input is activated using another ReLU function. The following block then receives the output from the residual block.

3.2.3 Fully Connected Layer

The output from the previous residual block is mapped to the output classes by the network's last, completely linked layer. The number of output classes is the same as the number of neurons in the fully linked layer. ResNet-50 is known for its skip connections, often called identity connections. They enable the network to develop more accurate representations of the input data by preserving information from previous layers. A skip connection is formed by combining the outputs of earlier and later layers.

Using the BUSI ultrasound dataset, the transfer learning-based breast cancer detection system built with the ResNet50 architecture showed encouraging results. The system successfully classified breast tissue into three categories—normal, malignant, and benign—by using pretrained weights and optimizing the framework using medical imaging data. The predicted class and the probability score that represents the forecast's confidence (certainty) are both included in the model's prediction output. The system continuously produced accurate classifications during testing, with confidence levels for correctly tagged samples frequently over 95%. Resizing, normalization, and batch dimension expansion are examples of image preprocessing techniques that helped standardize the input and greatly enhanced model performance. After taking into consideration, the combination of ResNet50 and Flask-based deployment produced a productive, an intuitive online application, can aid in the early detection of breast cancer utilizing ultrasound images. This technology shows the promise of deep learning in real-time healthcare diagnostics in addition to supporting clinical decision-making.

4. Results and Discussion

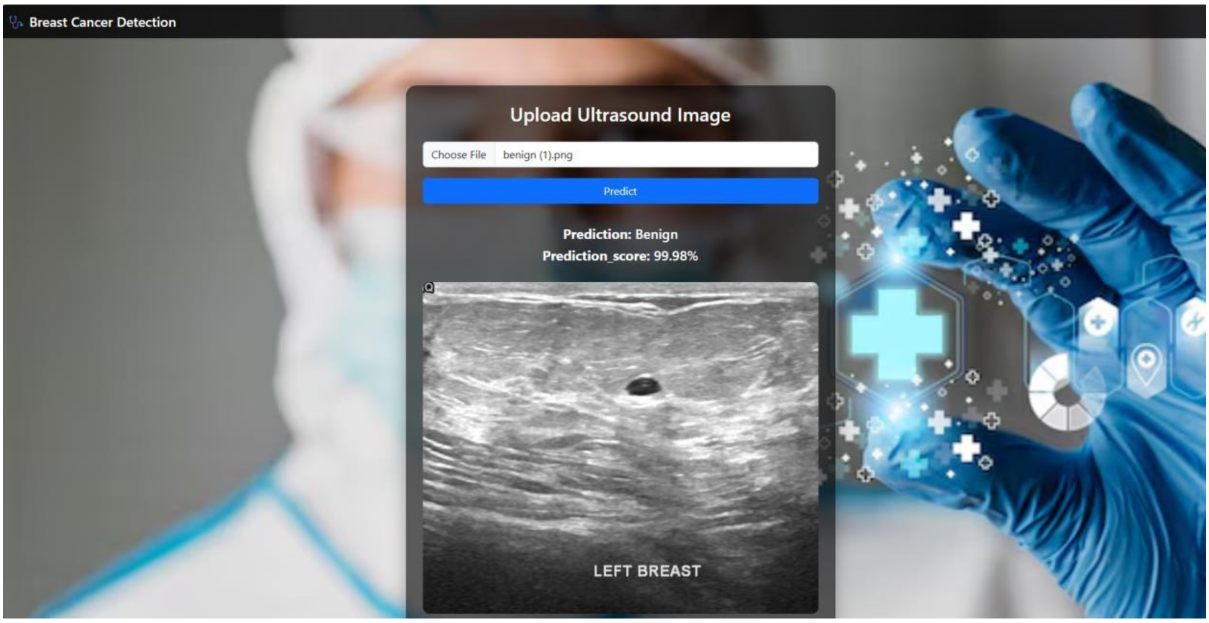

Figure 2

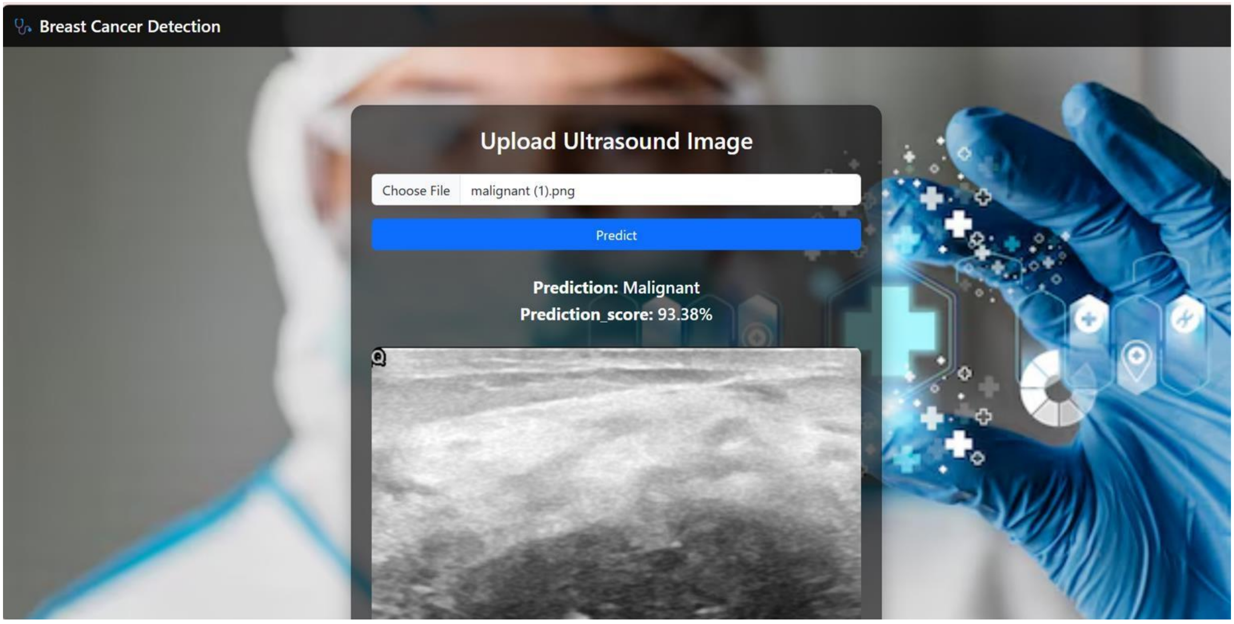

Figure 3

The image shows the result of image segmentation using the ResNet-50 Architecture. Figure 2 and 3 displays the input images, which are ultrasound pictures of breast cancer in both its benign and malignant stages are being predicted.

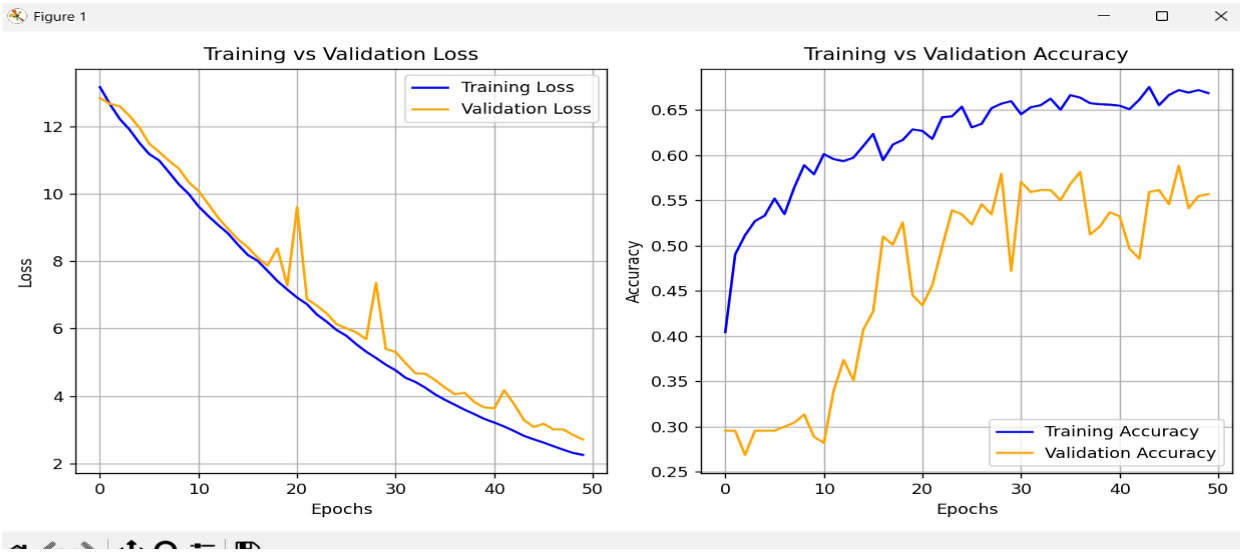

Figure 4

In the Figure 4 the x axis of the graph represents the Epochs and y axis represents the training loss in the 1st graph, and the 2nd graph has it's x axis as epochs and y axis as accuracy we can see that by the usage of ResNet50 architecture the training loss decreases whereas the training accuracy increases.

5. Conclusion

This study demonstrates how deep learning and transfer learning approaches are employed in the analysis of medical images, specifically for ultrasound image-based breast cancer evaluation. The system was able to extract deep characteristics and provide high-accuracy predictions across three crucial classes—normal, malignant, and benign—by leveraging the ResNet50 architecture. The system's usability is improved by integrating a straightforward and interactive online interface using Flask, opening it up for either clinical usage or more research. This effort not only demonstrates how artificial intelligence may help with breast cancer early detection, but it also provides a good foundation for future upgrades, such as incorporating larger datasets. real-time camera input, or smartphone integration. Overall, it contributes significantly to the growing field of AI-powered medical diagnostics.

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