Breast Cancer Image Analysis for Tumor Detection

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***Abstract*—Breast Cancer remains to be one of the most critical and leading causes of cancer-related deaths amongst female individuals worldwide. In the field of medical imaging, much progress has been made to ensure that there is a reduced number of such cases and early detection scenarios. In the current medical space, there is a combination of using computer-aided-diagnosis, as well as manual detection of breast ultrasound images in terms of capturing key details on tumors. In this research, we are presenting a deep learning approach that can pro-actively allow us to classify breast ultrasound images into one of the following categories: benign, malignant, and normal. This is primarily achieved by a well-performing ResNet-50 classifier that was used in this research. The core of this project includes using raw images from the static dataset, applying advanced image processing techniques, overlaying these images, and training the classifier. The results of this research demonstrate the high capabilities deep learning methodologies in breast ultrasound image classification, which have seen achieve well-established and quantifiable evaluation metrics that showcase the features of a high-quality model. (*Abstract*)**

Keywords—Breast Cancer, Ultrasound Imaging, Image Processing, Image Classification, ResNet-50, Evaluation Metrics

I. Introduction

Breast Cancer is one of the most brutally common scenarios of diagnosing with cancer in females. With the increasing number of diagnosis in this field, there is also increasing number of deaths that a registered due to this cancer which comes alongside tumor development. Hence, the field of early detection and automated diagnosis has totally evolved and revolutionized the way medical experts provide and learn about cancer related patients. Ultrasound images itself has various number of challenges. When closely looked at from an image processing perspective, these ultrasound images tend to be prone to high levels of noise, lower ends of contrast and variability in interpretation. The most challenging part is to deal with the variability in interpretation, which essentially suggests that if you have two medical experts analyzing the medical image, it is highly possible that both of them may conclude in extremely conflicting opinions. When automating processes it is important to stick to a common and strict ruleset, which leaves little room for variability of interpretation and subjective opinions. However, ultrasound imaging has dominated this space as is used as the preferred screening method primarily due to its non-invasive nature, affordability, and its extensive capabilities to detect tumors in dense breast tissues, where advanced methods such as mammography often comes with inaccuracies and failures. formatter Computer-aided diagnosis systems powered by deep learning models are able to leverage ultrasound images to accurately classify and detect tumors in breast tissues. This research project utilizes a specific type of model, it is utilizing the ResNet-50, which is a deep convolutional neural network (CNN), in order to classify and better understand breast ultrasound images with tumors. It is important to note that these breast ultrasound images are segmented into three different categories.

1) ***Benign*** *(non-cancerous growth)*
2) ***Malignant****(cancerous tumors)*
3) ***Norma****l (healthy tissue)*

In order to enhance the model classification performance, we need to ensure that we are using advanced image preprocessing methodologies before feeding any input images into the model. This is a core part of the project as we move forward.

The key objectives of this research project include:
(a) Develop an automated deep learning model for breast ultrasound image classification and tumor detection.
(b) Improve and produce high quality classification model performance by using advanced image processing techniques
(c) Evaluate the performance metrics of our classification model and identify how well it performs in tumor detection.

This particular research project contributes to the growing to the field of artificial intelligence and machine learning in medical imaging by demonstrating highly efficient breast ultrasound image classification.

II. BACKGROUND

A. Breast Cancer & The Need for Early Detection

Breast cancer is the second on the list of cancer-related deaths in females around the world with approximately 2.3 million new cases worldwide annually. Early detection by utilizing automated image analysis and techniques can aid in significantly reducing the mortality rates, essentially providing room for timely intervention. When detecting tumors for breast cancer, the screening methods include: Mammography, MRI, Ultrasound Imaging. While mammography can be considered the gold standard, the more prevalent screening method is ultrasound images that suffer in terms of resolution and noise.

B. Deep Learning in Medical Imaging

The current trajectory of the medical field when it comes to incorporating Deep Learning models in the field of medical imaging has been revolutionized. The introduction of deep learning models such as the Convolutional Neural Network (CNNs), have remarkably changed the way medical image analysis is carried out. It is important to note that unlike traditional machine learning approaches, which primarily rely on handcrafted feature extraction, the CNNs have a unique ability to automatically learn the spatial hierarchies of the features from the raw images, eventually producing and leading higher accuracies and better generalization.

It is important to note that fascinating advancements in the CNN-based medical imaging include the following:

(a) **VGGNet** – The first deep CNN for large scale image classification

(b) **InceptionNet** – much more improved accuracy with multi-scale feature extraction

(c) **ResNet** **-** Deep architectures with skip connections prevent vanishing gradients, making training easier.

In our research project, the utilization of the ResNet-50 model has been vital. It has also been widely adopted in the medical image classification field, because this pretrained model has robust feature extraction capabilities and pretrained ImageNet weights which allow quicker convergence on relatively smaller datasets.

C. Exisiting Research on Breast Ultrasound Classification

Traditional image processing techniques often require large amounts of manual feature extraction which can be extremely time consuming depending on the size of dataset. However, Deep Learning particularly utilizes the Convolutional Neural Networks, which allows for automatic learning features from the images.

Wang et al. (2024) demonstrated the power of deep transfer learning with DenseNet to classify images of breast cancer. Their model had achieved ~84% accuracy and demonstrated that the pretrained networks were able to classify medical images efficiently even with small and restricted datasets.

Ashraf et al. (2024) proposed a new approach by combining ResNet-50 with a Naive Inception module and obtained 98% accuracy. Their work proves the effectiveness of hybrid deep learning models and self-supervised learning in improving classification performance.

My work was aimed at outperforming the above work that employs transfer learning with ResNet-50 by taking advantage of its effective feature extraction but combining it with more recent image preprocessing techniques like CLAHE, adaptive thresholding, noise removal, and overlaying images in order to further enhance accuracy in the classification model.

All in all the turning part of this research project and what makes it different and highly important in my opinion is that that the overlaying of images on top of each other alongside advanced preprocessing can lead to best and ultimately an effective classification model.

III. METHODOLOGY

This section outlines the step-by-step approach which is used for breast ultrasound image classification using the ResNet-50 pre-trained model. This methodology consists of image preprocessing, image enhancement, image segmentations, overlaying images, model training, evaluation metrics. A figure below can clearly highlight the methodology.

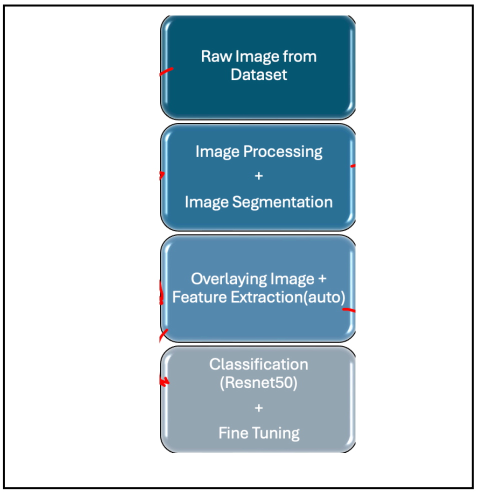

Figure 1: Image Processing Pipeline

A. Raw Images from the Dataset

The dataset that was utilized for this project is the Breast Ultrasound Dataset, which composes of images and segmented masks for each corresponding class: **benign**, **malignant**, **normal**. The corresponding masks clearly highlights and demonstrates a region of interest. Here are some important points about the dataset:

(a) **No. of Images :** 780 images

(b) **No. of Patients:** 600 female patients

(c) **Age Range of Patients:** 25-75 years

(d) **Collection Year:** 2018

(e) **Image Size:** Avg size ~ 500 x 500 pixels

It is important to note that these raw images were not fed into the deep learning model directly, rather they went under several image processing techniques to provide us with optimal performance.

B. Image Processing & Image Enhancement

In order to better and enhance the quality of the images, the following preprocessing steps were applied:

- **Standardized Resizing**: All selected images were resized to standardized dimensions to match the input for the ResNet-50 pre-trained model.
- **Histogram Equalization**: Contrast enhancement (CLAHE) was utilized to help assist in better visibility.
- **Noise Reduction:** Median and Gaussian filtering were applied to remove and reduce the noise in the Ultrasound Images.
- **Edge Detection:** Canny Edge Detection was applied to selectively highlight tumor boundaries.
- **Morphological Operations:** Used to refine segmentation masks and remove smaller artifacts. These were more focused on the mask itself.
- **Data Augmentations (flips):** This was used in order to broaden and expand the dataset, and maybe help with the minority classes in our dataset.

Identify applicable funding agency here. If none, delete this text box.

C. Image Segmentation

Each ultrasound image scan in our dataset came alongside with a corresponding mask, which selectively conveyed region of interest as in isolate the tumor region from the background directly. Overall, the Image Segmentation process included of the following:

1) Overlaying the segmented mask onto the original ultrasound scan.

2) Implement and utilize morphological operations to further clean up and reduce noise.

3) Clearly extracting only the Region of Interest.

As you can see from the figures below, these images show how the processing and overlay techniques enable visualization of different breast tissue categories —benign, malignant, and normal.

In **Figure (2)** the benign lesion is shown with its corresponding mask and a processed overlay that marks the edges and texture of the benign tissue.

Figure (3) reveals a malignant tumor, with mask dividing the suspected region and superimposed processed image indicating characteristic features of malignancy.

Finally, **Figure (4)** reveals a healthy breast ultrasound scan, its mask, and overlaid result displaying the characteristic less complex texture and boundary patterns of a normal tissue with no specific tumors that can be detected.

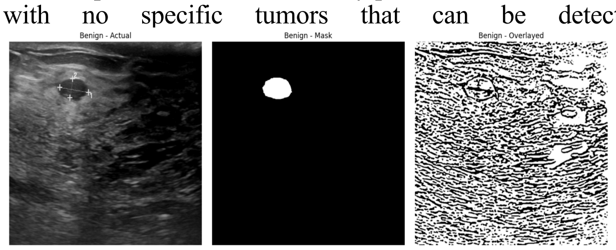

Figure 2: Benign Overlayed Processed Image

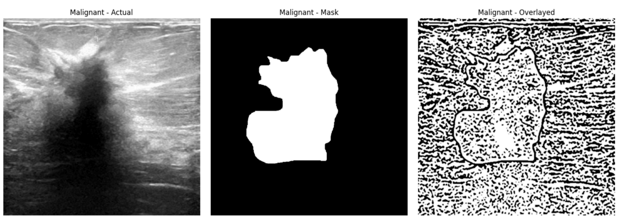

Figure 3: Malignant Overlayed Processed Image

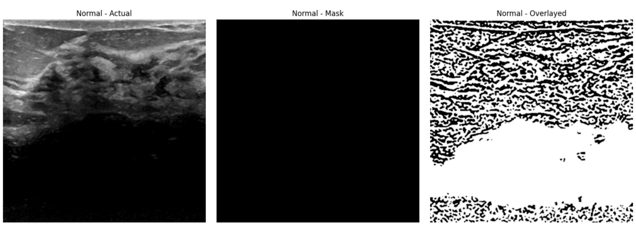

Figure 4: Normal Overlayed Processed Image

D. Automated Feature Extraction & Deep Learning Model

In terms of classification purposes, we utilized the ResNet-50, a deep convolutional neural network (CNN). The fully connected layer, which is a part of the model architecture was specifically modified to match and handle the three-class classification problem — Benign, Malignant, Normal.

To understand the model in a more detailed manner, let's break down the Model Architecture as follows:

- **Base Network:** Pre-trained ResNet-50 (initial layers)
- **Fully Connected Layer:** Modified to handle a three- class classification problem.
- **Loss Function:** Utilizing the Cross-Entropy Loss
- **Optimizer:** SGD (momentum=0.9)
- **Learning Rate Scheduler:** StepLR which decays every 5 epochs by 0.1

The total number of epochs that was used was **10 epochs**. As per multiple run time analysis, this deemed to be sufficient.

E. Training & Evaluation

For model training, the data was split into **72.25%** (training), **12.75%** (validation), and **15%** (test) sets to ensure an equally balanced test for the model. This can be demonstrated below in Figure (5).

```
train set:
benign: 315 files
malignant: 152 files
normal: 96 files

validation set:
benign: 56 files
malignant: 27 files
normal: 17 files

test set:
benign: 66 files
malignant: 31 files
normal: 20 files
```

Figure 5: No. of Files

The training set was used for training the model parameters, while the validation set was used for hyperparameter tuning and performance checking.

Finally, the test set was used for final testing to measure generalization. The network was trained using Stochastic Gradient Descent (SGD) optimizer with batch size 8 for 10 iterations for successful network updating without overfitting.

A fixed number of epochs was used instead of early stopping to maintain experiment consistency. This decision was made basically using trial and error and running these models' multiple times. Google Collab was utilized to guide the training was conducted over for better computation, allowing for smoother runs.

To evaluate model performance, certain important metrics were utilized. The classification report provided information regarding precision, recall, F1-score, and accuracy for each class. A confusion matrix was also derived to analyze misclassifications and identify the model's ability in distinguishing benign, malignant, and normal cases. All these metrics combined utilized to determine how effective the ResNet-50 model is in breast ultrasound classification. These evaluation metrics are extremely useful because in field of diagnosis of medical conditions, a false negative (incorrect tumor prediction) is much more risky than a false positive (benign case incorrectly predicted). These measures facilitate tuning and evaluating the model so that false negatives are minimized with high accuracy of classification of tumors.

IV. RESULTS

The results would be highlighting the quantitative and qualitative results obtained from training and evaluating the ResNet-50 based on tumor detection classifier. Overall, the goal was to improve the classification accuracy through multiple iterations and essentially end up with the most improved classification accuracy through the advanced image processing techniques alongside using convolutional neural networks.

It is important to keep in mind, that there were multiple iterations before these results where achieved. There were multiple instances of changing the no. of epochs, changing the splits between the test, validation, and training sets. There was times were this was done incorrectly and lead to faulty results as well. However, through multiple iterations and learnings it is fair to conclude that the following results are the most improved results of this research project.

A. *Quantative Results*

At the current and final stage of this project, this is what the current classification report looks like:

```
classification report:
              precision    recall  f1-score   support

      benign       0.83      0.89      0.86        66
   malignant       0.86      0.58      0.69        31
      normal       0.72      0.90      0.80        20

    accuracy                           0.81       117
   macro avg       0.80      0.79      0.78       117
weighted avg       0.82      0.81      0.81       117
```

An overall accuracy of ~81% was achieved. This is indicative of good classification performance. The highest reported validation accuracy was ~88%.

Figure 6: Classification Performance

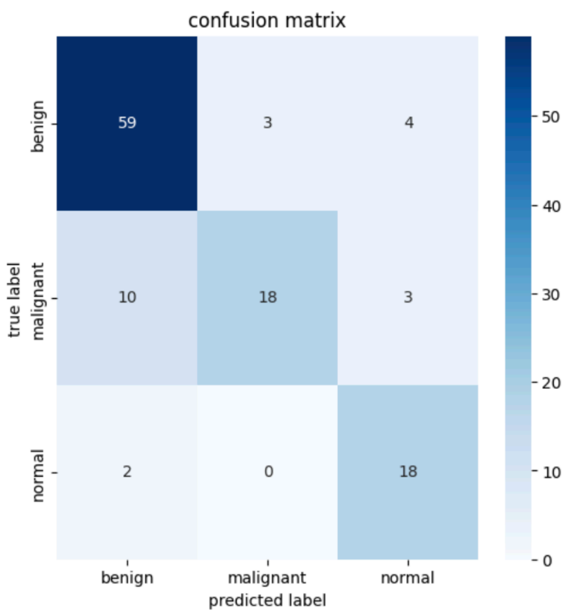

Figure 7: Confusion Matrix Analysis

A key issue to be pointed out from this confusion matrix is that is highly relevant to medical field is that a lot of the malignant cases where incorrectly classified which can be an extremely critical situation. Hence, it is clear that there is a lot of room for improvement, and this scenario needs to be handled more carefully in terms of classification purposes.

B. *Qualitative Results*

This looks at the actual cases where it can be analyzed directly and understand more about the classifiers performance to correctly identify the actual vs predicted classes and gives us guidance on how this classifier may way work in a real-world scenario.

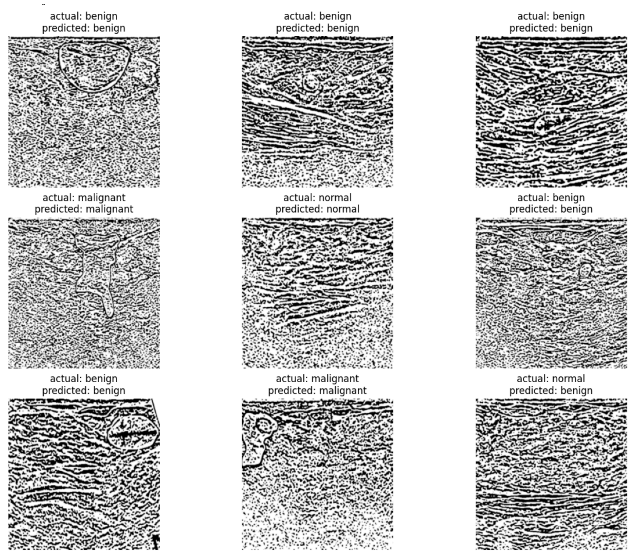

Figure 8: Actual vs Predicted Cases

As we can observe in Figure (8), we still have some inconsistencies with the model and some incorrect classifications which are extremely critical and have been explained above. The main issue comes when malignant cases are misclassified. Although, the model shows high accuracy in classifying benign and normal cases.

V. CONCLUSION

In conclusion, our classification model achieved an overall accuracy of **81%**, which is indicative of good classification performance. Benign cases had the best recall ~89%, benign tumors were correctly classified with minimal false negatives. However, malignant cases showed the worst recall (58%) , which means malignant tumors were misclassified, which is a critical issue in medical diagnosis. All in all, through better image processing and trying out different pretrained CNN's better classification accuracies may be achieved to helped deal with the malignant tumor misclassifications which is extremely critical.

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VII. REFERENCES

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