DATS 6303

Breast Cancer Ultrasound Classification - Individual Report

GROUP #5

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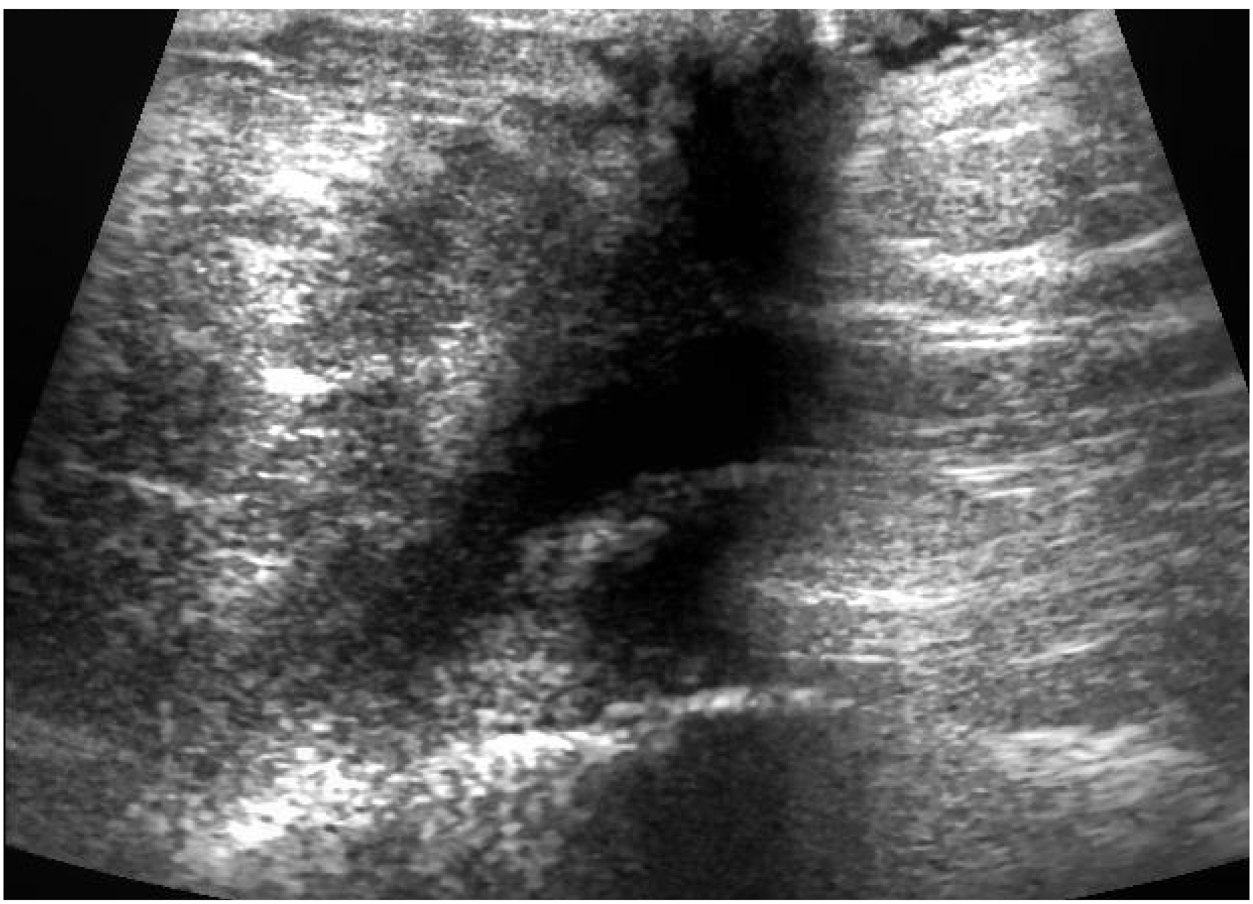

Introduction

The goal of this project was to utilize deep learning and computer vision techniques to detect breast cancer from ultrasound images. Breast cancer is a significant public health concern that causes millions of new cases each year. Early detection of the disease is essential to survival, with a five year survival rate of 99% for localized tumors found in early stages. In order to properly combat breast cancer, developing screening techniques to accurately detect potential malignant tumors is essential to treat the millions who are affected with breast cancer around the world.

While current breast cancer screenings are very accurate at detecting cancer, they are usually invasive techniques that are uncomfortable for the recipient. This could potentially deter people from getting screenings that they need. If we were to develop a technology that is less invasive, like an ultrasound, it could make screenings more efficient and provide access to more people who need it. Combining these images with deep learning technology would help with diagnosis and allow for early treatment.

Individual Work

Alejandra and I collaborated on most of the project. It began with both of us finding different datasets brainstorming different ideas for the project. Once this was decided upon we started working on the code in our github. Alejandra developed the initial code structure for the training of the model, which I then built upon and allowed for an improvement of our model performance. We documented the helper functions that we created in our Toolbox.py file in the Code folder, with the actual training being done in Code.py. After this, we both worked on different augmentation techniques, such as flipping, rotating, normalization, and experimenting with brightness, contrast, and saturation. Afterwards, we utilized these techniques alongside the balancing techniques which helped improve our model.

After experimenting with augmentation, Alejandra was able to generate the overlaid images that are described in the initial report. Once these images were generated, she ran an updated model using these images instead of the original images. Afterwards, I created updated metrics to test the two models on our holdout test dataset.

After we finalized our models, Alejandra worked on the side deck while I worked on getting the streamlit UI organized and running. I organized all of the metrics and wrote the code for the demo in order for predictions to be made directly in the UI. After this we finalized the slide deck to prepare for the presentation.

Results

We ended up with two models, one of which was trained on the original ultrasound images, and the second was trained with the mask ground truth images overlaid on the original images. The original model had moderately good results with an F1 macro score around 0.78. The second model had much better results with an F1 score at 0.98. The results of both of these models are shown in tables 1-4.

Table 1. Macro Metrics for Performance of Model 1.

	Metric	Value
0	Accuracy	0.7265
1	Precision	0.7372
2	Recall	0.7265
3	F1 Score	0.7295

Table 2. Class Metrics for Performance of Model 1.

	Precision	Recall	F1 Score
Benign	0.8300	0.7400	0.7800
Malignant	0.6000	0.6600	0.6200
Normal	0.6700	0.7700	0.7200

Table 3. Macro Metrics for Performance of Model 2.

	Metric	Value
0	Accuracy	0.9786
1	Precision	0.9786
2	Recall	0.9786
3	F1 Score	0.9786

Table 4. Class Metrics for Performance of Model 2.

	Precision	Recall	F1 Score
Benign	0.9800	0.9900	0.9800
Malignant	0.9700	0.9500	0.9600
Normal	1.0000	1.0000	1.0000

Summary and Conclusions

The results of these models show the significant potential that deep learning techniques have for breast cancer screenings. Being able to screen cancer with just ultrasound images would make this practice less invasive and more accessible to people around the world. We experienced some limitations in this project, including the size of this dataset. While more would be done to actually utilize data like this, its a step in the right direction to show the utility of computer vision in cancer screenings.

Code Percentage

The percentage of code I used from the internet was 20%, much of which was modified to accommodate the structure of our files and models.

NOTE: I was making commits in the terminal, so some of my commits were made under the username “Ubuntu” rather than “jmcmorrow”.

References

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