Embedded System for Ultrasound Breast Cancer Diagnosis

Bachelor Thesis

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***Abstract*—Early diagnosis of breast cancer plays a crucial role in improving patient outcomes and survival rates. The integration of artificial intelligence (AI) in medical imaging opens up new opportunities for enhancing diagnostic accuracy and accessibility. Consequently, an accurate, affordable, and portable breast cancer diagnosis system would improve the survival rates and overall quality of life for many patients. While many studies have reported high accuracy using convolutional neural networks (CNNs) on limited datasets, the ability of these models to generalize effectively remains a concern. In this study, five diverse datasets (BUSI, BUS_UC, BUS_WHU, BUS-UCLM, and BUSBRA) were utilized for training, and an extra dataset called Dataset B was reserved for system evaluation. The proposed system adopts a two-stage classification approach, distinguishing between abnormal and normal images initially, followed by benign and malignant classification if abnormalities are detected. The system features two highly advanced pretrained models: ResNet-101 and InceptionV3. The system has achieved accuracies of 99.31% and 86% for stage 1 and stage 2 models, respectively, and 88% when evaluating the whole system. To enhance accessibility, the models were converted to TFLite and deployed on a Raspberry Pi 3 with a user-friendly graphical interface for instant diagnosis.**

***Index Terms*—Breast cancer diagnosis, artificial intelligence, convolutional neural networks, ResNet101, InceptionV3, TFLite, Raspberry Pi, medical imaging, portable diagnosis system**

I. Introduction

In 2020, the World Cancer Research Fund reported that breast cancer is the most common type of cancer in the world, with over 2 million cases, breast cancer alone makes up 12.5% of all new cases recorded in 2020 and 25.8% of new cases in women [1]. The decision to pursue this project was motivated by the need for affordable, improved, and accessible methods of diagnosing breast cancer, which can be used by individuals inside and outside the medical profession. With that being said, early detection of breast cancer significantly improves the chance of survival, however around 50% of cancers are still only detected at a later stage [2]. There is a clear incentive to develop innovative solutions that can reach a wider population. By focusing on affordability, accuracy and portability, this project aims to help more people get access to diagnostic services for breast cancer, which will make healthcare better for everyone.

Furthermore, recent advances in artificial intelligence and machine learning offer a great opportunity to change how we diagnose breast cancer. With these technologies, we can create tools that are not only affordable but also accurate at spotting cancer early. By using AI to analyze ultrasounds, we can improve the chances of finding early signs of cancer that might be hard for humans to see. This project seeks to use these innovations to develop a comprehensive diagnostic system that can be deployed in various settings, from urban hospitals to patients. By making cutting-edge technology accessible to a wider audience, we can contribute to the early detection and treatment of breast cancer, ultimately saving lives and reducing healthcare disparities.

This study aims to develop a deep learning model for the classification and diagnosis of breast cancer using ultrasound images by leveraging the newest deep learning models available. Specifically, we will use existing models that are already trained and adjust them for breast cancer diagnosis, applying Transfer Learning concepts to adapt their capabilities to our specific task. we aim to make the classification process better and more accurate. The primary objective is to find whether an ultrasound shows a tumor or not, if it does it should analyze the tumor and output if its cancerous or not. The model will be trained using various datasets to increase it's ability to generalize to ultrasound images taken with different devices.

This work was supported by the Information Technology Industry Development Agency (ITIDA) under the ITAC program.

The finalized model will be deployed onto a Raspberry Pi device. This implementation will make it easy to connect with handheld ultrasound devices, allowing for immediate diagnosis of breast cancer. Additionally, the model's output will be displayed on a screen, providing accessible results to end-users.

II. Previous Work

A. Discussion

Prior to starting our research, we reviewed 30 papers related to this study. However, for brevity and to focus on the most relevant contributions, only the most significant studies are mentioned. Nasim Sirjani et al. (2023) [3] proposed a new improved InceptionV3 architecture, they converted the InceptionV3 modules to residual inception ones, increased their number, and altered the hyperparameters, they used five datasets including two prepared from different imaging centers. They reported 81% accuracy. Walid Al-Dhabyani et al. (2019) [4] compared five deep learning models AlexNet, VGG16, Inception, ResNet, NASNet, using pretrained weights for the latter four. They also tested on four forms of data samples, the best results were achieved by using a pretrained NASNet Model on a combination of BUSI and Dataset B with DAGAN Augmentation, which was 99% Accuracy. Tomoyuki Fujioka et al. (2019) [5] used GoogLeNet which is essentially InceptionV1, the dataset consisted of multi-view images of benign and malignant tumors that sums up to 947 images. The accuracy achieved by this approach is 92.5%. In the paper published by Se Woon Cho et al. (2022) [6], they proposed a multi-stage approach for segmentation, the first stage is classification using an ensemble of DenseNet121 and ResNet101, the proposed ensemble model is called BTEC-Net and the classification was used to predict abnormal ultrasound images to later be used in stage 2 which is segmentation using UNet. They used the dataset BUSI and reported 99.487% accuracy in Stage 1. Ikram Ben Ahmed et al. (2022) [7] published a study that uses ResNet50 using pretrained weights, they used 780 Images from the BUSI Dataset and achieved 93.65% Accuracy. Lana Alhaj Hussain et al. (2020) [8] deployed an InceptionV3 model trained on 33984 images on a Raspberry Pi 4 B, achieving 94% Accuracy and only two seconds per image. Table I shows a summary of the methods, datasets and results of the previously mentioned studies.

B. Research Gap

Many studies in this literature review relied on a limited number of datasets, often one or two, which may restrict their models' ability to generalize, leading to potential overfitting to specific dataset features and poor performance on unseen data. Additionally, a significant proportion of these studies used private datasets, which may prevent other researchers from replicating and building onto their results which could slow down further advancements in the field. In contrast, this project uses six different publicly available datasets collected from different countries, also the model is tested on a completely unseen dataset to accurately measure its performance. Furthermore, despite the rising interest in deep learning in the medical field, there's a noticeable absence of studies specifically addressing breast cancer diagnosis on edge devices. This gap in research provides an opportunity for future investigations to examine the effectiveness and usefulness of deploying breast cancer diagnosis models on edge devices.

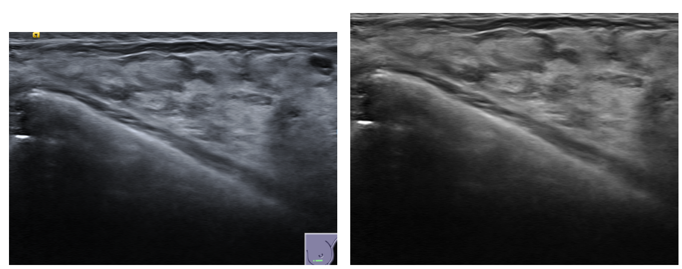
III. Methodology

A. Dataset Acquisition

This research combines six datasets from different countries, collected using various ultrasound devices. Initially, only the BUSI dataset was used for training and testing then Dataset (B) was introduced to assess how well the model could perform on unseen data. However, the results showed poor generalization, highlighting the need to include more datasets. The new datasets are: BUS_UC, BUS_WHU, BUS-UCLM, BUSBRA.

B. Preprocessing

For the first stage, benign and malignant images were collected from all datasets mentioned except BUS-UCLM, as the images contained extra shapes that couldn't be cropped without potentially cropping out parts of the tumor too. The images were all combined into a single class, "abnormal," while the normal classes of BUS-UCLM and BUSI were combined to form the other class, "normal". Images were first cropped to remove unwanted shapes from the normal class in the BUS-UCLM dataset, and then converted to grayscale. The dataset was then manually cleaned to remove any remaining outliers. Lastly, to address class imbalance, the "normal" class was augmented using transformations such as flipping, random resized cropping, and random adjustments in brightness, contrast, saturation, and hue. For the second stage, benign and malignant images were only combined from BUSI, BUS_UC and BUSBRA, they were also manually cleaned to remove all outliers such as images with arrows pointing at the tumor.



Original Image Processed Image

Fig. 1: Sample Image from BUS-UCLM before and after preprocessing.

C. Multi-stage Classification

The first step in the process involves using a pretrained ResNet-101 for determining whether an ultrasound image is within normal parameters or shows abnormalities suggestive of tumor presence. The dataset is divided into two classes: normal and abnormal. If an image is labelled as "normal" it's

TABLE I: Summary of some of the studies reviewed.

Ref	Year	Models	Dataset	Accuracy
[3]	2023	Improved InceptionV3	BUSI, Dataset B & 3 Unnamed Datasets	83%
[4]	2019	NASNet	BUSI Dataset (B)	99%
[5]	2019	GoogLeNet	Custom Dataset 947 Images	92.5%
[6]	2022	BTEC-Net	BUSI 780 Images	99.487%
[7]	2022	ResNet-50	BUSI	93.65%
[8]	2020	InceptionV3	Multiple Datasets 33,984 Images	94%

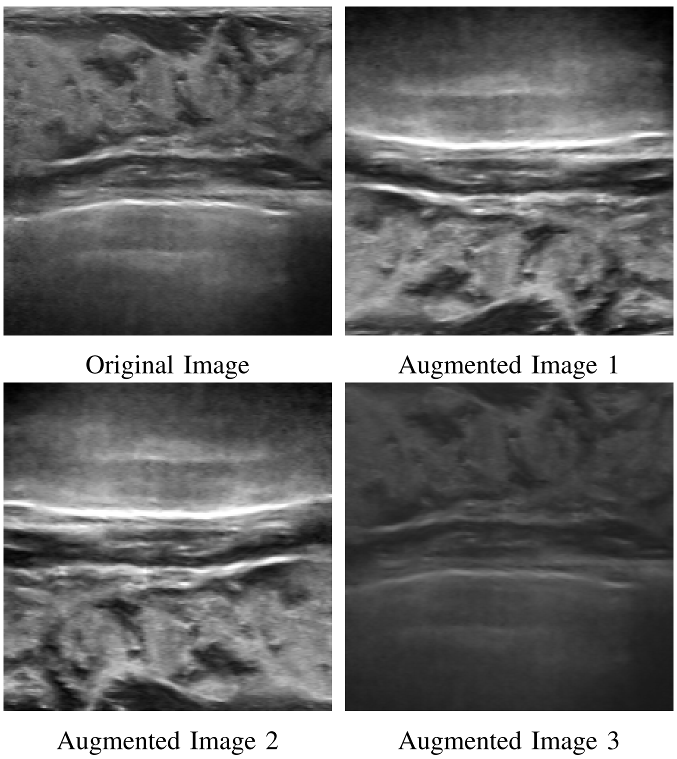


Fig. 2: Examples of the Augmented Images.

excluded from the rest of the process. The dataset was split randomly into 80% training, 10% testing and 10% validation. The model's fully connected layer was modified to add two dense layers with ReLU activation function, and two dropout layers and finally one last dense layer with a sigmoid activation function, the dropout layers have a 50% drop chance to combat overfitting. In order to yield the most accurate results many tests were conducted using different hyperparameters and models.

In the second stage of the diagnosis process, the dataset is divided into two classes: benign and malignant. The model used was a pretrained InceptionV3 Model, the weights used were from training it on the imagenet dataset. The dataset was split randomly into 80% training, 10% testing and 10% validation. This model's fully connected layer was also modified

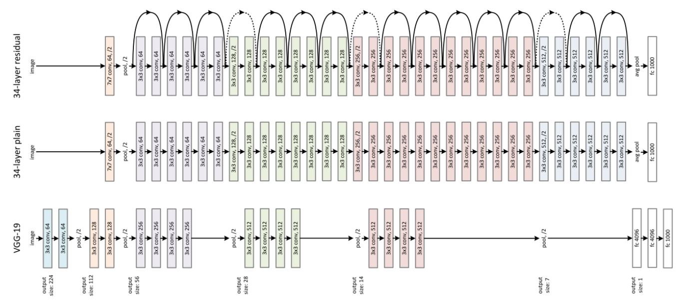


Fig. 3: Illustration of the architecture of ResNet-34 in comparison to other CNNs [9].

to add two dense layers with ReLU activation function, two dropout layers, two Batch Normalization layers immediately before the ReLU activation functions and finally one last dense layer with a sigmoid activation function, the dropout layers also have a 50% drop chance to combat overfitting.

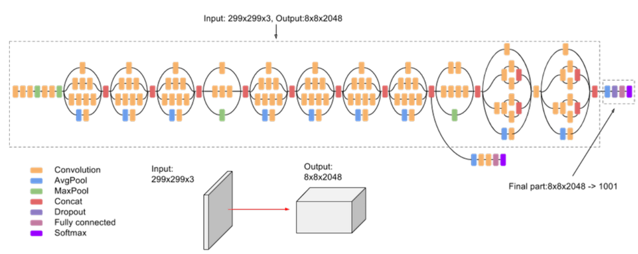


Fig. 4: Illustration of the architecture of InceptionV3 [10].

D. Deployment

For the deployment on the Raspberry Pi 3 B+, I began by configuring the device using the official Raspberry Pi Imager tool [11]. With this tool, I installed the latest release of Raspberry Pi OS (64-bit) onto the Raspberry Pi's 32GB microSD card. This step ensured that the operating system was up to date and compatible with the project requirements. After the installation, We created a python environment and started installing the necessary packages and updating the system packages to ensure optimal performance and security.

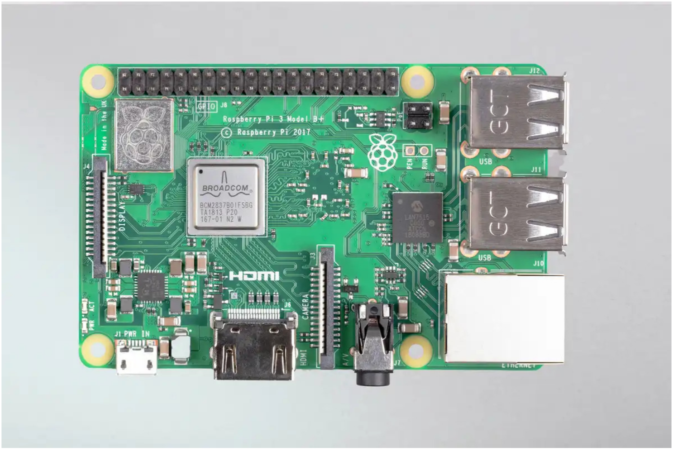


Fig. 5: The Raspberry Pi 3 B+ Device [12].

The deployment process involves several key steps. Firstly, for optimization, we converted both TensorFlow models to TensorFlow Lite. Then, the lite version is transferred to the Raspberry Pi using a USB Flash Drive.

The user interface was developed using Tkinter, a lightweight and user-friendly GUI toolkit for Python. The GUI was designed to allow users to input an image and immediately view the results after processing in a user-friendly manner. This streamlined approach provides users with a great experience, making the interaction with the application intuitive and easy.

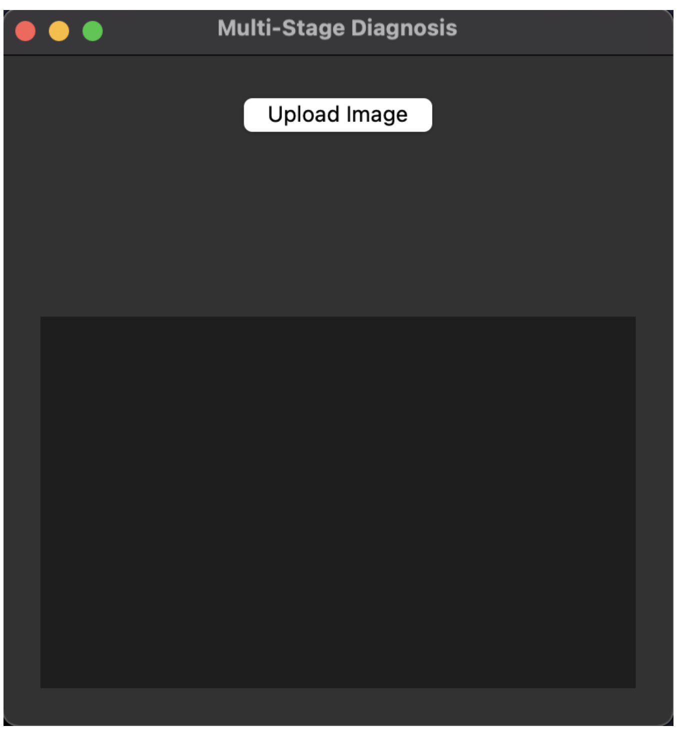


Fig. 6: The Graphical User Interface.

IV. Exprimental Results

A. Tools Used

1) Kaggle: Kaggle is an online platform that hosts data science competitions, datasets, and collaborative coding environments. It provides many accelerator options such as GPU T4 x2, GPU P100 and TPU VM v3-8.

2) Tensorflow: TensorFlow is an open-source software library for machine learning and AI.

3) Matplotlib: Matplotlib is a plotting library for Python. It provides functions for creating graphs and visualizing data.

4) Tkinter: Tkinter is a Python binding to the Tk GUI toolkit, which is the standard Python interface to the Tk GUI toolkit, it's used in this project to build a GUI for the users to navigate through.

5) Raspberry Pi 3 Model B+: The Raspberry Pi 3 Model B+ is a versatile and affordable single-board computer. The features include: a quad-core ARM Cortex-A53 CPU, 1GB of RAM, built-in Wifi and Bluetooth connectivity, GPIO pins for interfacing with external devices.

B. Dataset

- BUSI [13]: Collected in 2018 from 600 female patients. It consists of 780 PNG images and the ground truth images, with an average size of 500x500 pixels. The images are labelled benign, malignant or normal.
- Dataset B [14]: This dataset is managed by UDIAT-Centre Diagnostic, Corporacio Parc Tauli, Sabadell (Spain), it consists of 163 ultrasound images and the ground truth images, comprising 53 malignant and 110 benign cases.
- BUS_UC [15]: The BUS_UC dataset consists of 358 benign and 453 malignant tumor images, all at a resolution of 256×256 pixels. Sourced from Ultrasound Cases (ultrasoundcases.info), the dataset lacks ground truth images, but annotations by an experienced radiologist enable segmentation and classification tasks for both benign and malignant tumors.
- BUS_WHU [16]: Breast cancer ultrasound images were gathered from Renmin Hospital of Wuhan University's radiology department between December 2020 and December 2022. The dataset comprises 927 images, covering both benign and malignant cases from patients aged 17 to 79. Ethical approval was obtained from the hospital's ethics committee (WDRY2022-K217). Each image contains tumor regions with varying area and morphology features such as contrast, brightness, and fuzziness, making it suitable for segmentation tasks.
- BUS-UCLM [17]: The dataset comprises 683 breast ultrasound images from 38 patients, with 174 benign, 90 malignant, and 419 normal cases. Real Scans were obtained using a Siemens ACUSON S2000TM Ultrasound System between 2022 and 2023. Ground truth segmentation masks label lesions, aiding in breast cancer research and model development.
- BUSBRA [18]: The BUS dataset from Rio de Janeiro's National Institute of Cancer comprises 1875 ultrasound

images from 1064 female patients, featuring 722 benign and 342 malignant cases. It includes BI-RADS assessments and manual lesion outlines for segmentation. The dataset offers 5- and 10-fold cross-validation partitions for CAD system evaluation.

TABLE II: Original Datasets Comparison

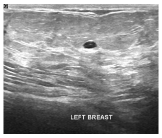
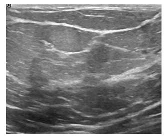
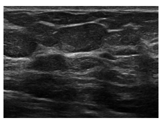
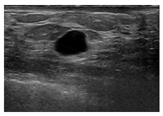
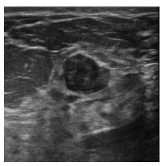
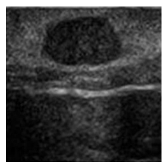
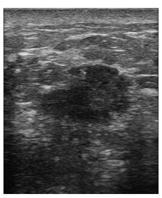
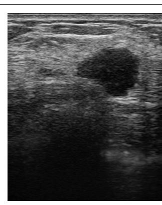
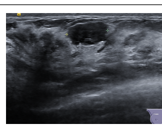
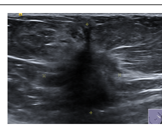
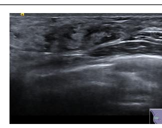
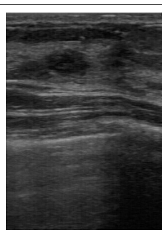
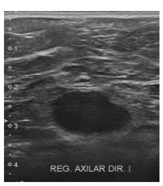
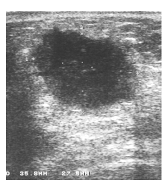
Dataset	Sample 1	Sample 2	Sample 3
BUSI			
Dataset B			
BUS_UC			
BUS_WHU			
BUS-UCLM			
BUSBRA			

TABLE III: Summary of Dataset Usage for Stage 1.

Dataset	Total	Abnormal	Normal
BUSI	649	519	130
BUS_UC	811	811	0
BUS_WHU	927	927	0
BUS-UCLM	387	0	387
BUSBRA	1875	1875	0
Data Augmentation	3619	0	3619
Total	8268	4132	4136

C. Stage 1 — Classification: Normal vs Abnormal

The dataset split is 70% training, 15% validation and 15% testing. As seen in TABLE VI, we managed to reach very low loss values using both ResNet-101 and NASNetMobile and the best loss was 0.02252, which we achieved during the first experiment. To combat overfitting and save the best model, two dropout layers with 0.5 dropout rate were added and early stopping was used alongside model checkpoints which are built into TensorFlow. In this stage ADAM was the optimizer selected with Binary Cross-Entropy loss function.

TABLE IV: Summary of Dataset Usage for Stage 2.

Dataset	Total	Benign	Malignant
BUSI	557	350	207
BUS_UC	628	218	410
BUSBRA	1275	676	599
Total	2460	1244	1216

TABLE V: Summary of Dataset Usage for the evaluation dataset.

Dataset	Total	Normal	Benign	Malignant
BUSI	45	45	0	0
Dataset B	120	0	77	43
Total	165	45	77	43

TABLE VI: Summary of the experiments conducted during Stage 1.

Experiment	Model	LR	Loss	ACC
1	ResNet101	0.00001	0.02252	0.9931
2	ResNet101	0.0001	0.0604	0.99
3	NASNetMobile	0.00001	0.0421	0.9878

D. Stage 2 — Classification: Benign vs Malignant

The dataset split is 80% training, 10% validation and 10% testing. As seen in TABLE VII, the performance of the models may seem poor in comparison to the first stage and to other models but that is because in this study we used three diverse datasets during the training process which may result in less accuracy and higher loss during the validation and testing stages but shows better loss and accuracy when tested on completely unseen data, indicating that the model is generalizing well. The models experimented with in this stage were InceptionV3, InceptionResNetV2 and NASNetMobile, with the best loss being 0.3804. To combat overfitting and save the best model, the same techniques used in stage 1 was used here, two dropout layers with 0.5 dropout rate were added in all experiments except experiment 6 which used 0.7 dropout rate, and early stopping was used alongside model checkpoints and in addition to that two batch normalization layers were also added and Binary Cross-Entropy was used as the loss function.

E. System Evaluation

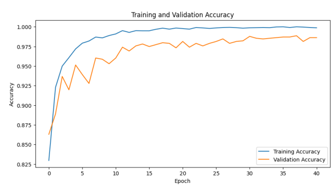
The best results obtained in Stage 1 were achieved using ResNet-101 with a learning rate of 0.00001, which resulted in a loss of 0.02252 and an accuracy of 99.31%. In Stage 2,

TABLE VII: Summary of the experiments conducted during Stage 2.

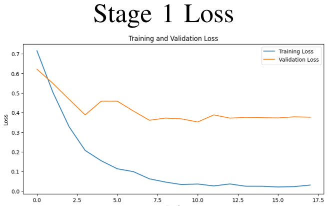
Experiment	Model	LR	Optimizer	Loss	ACC
1	InceptionV3	0.0001	Adam	0.4263	0.85
2	InceptionV3	0.0001	AdamW	0.4231	0.85
3	InceptionV3	0.001	Nadam, 0.9	0.69161	0.5
4	InceptionV3	0.001	SGD	0.5632	0.75
5	InceptionV3	0.0001	AdamW	0.3804	0.86
6	InceptionResNetV2	0.0001	AdamW	0.4497	0.82
7	NASNetMobile	0.00001	Adam	0.5897	0.67

the highest performance was observed with InceptionV3 using the AdamW optimizer with a learning rate of 0.0001, yielding a loss of 0.3804 and an accuracy of 86%. By combining the models from both stages, we achieved an overall model accuracy of 88% on Dataset B which wasn't used in training at all. Finally, the model was able to process each image within seconds after being deployed on the Raspberry Pi device, allowing for instant diagnosis.

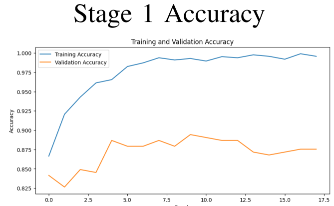
Stage 1 Loss



Stage 1 Accuracy



Stage 2 Loss



Stage 2 Accuracy

Fig. 7: Results from both stages.

V. Conclusion

In conclusion, we have designed and trained a system for breast cancer diagnosis using ultrasound images. The integration of this model with a Raspberry Pi facilitated real-time diagnosis, while the development of a user-friendly interface ensured accessibility for healthcare professionals and end-users. This work has contributed to the development of an efficient device for the early detection of breast cancer, potentially improving patient outcomes through timely diagnosis and intervention. As discussed in Chapter 3, the GUI allows users to input an image, which then undergoes several stages in the pipeline. First, the image is preprocessed to prepare it for the classification models. Next, a classification algorithm identifies any abnormalities present. If abnormalities are detected, the system further classifies them as benign or malignant. Finally, the diagnostic outcome is displayed on the screen, providing rapid feedback to the user.

A. Limitations

However, this study encountered several limitations worth noting. Primarily, many of the datasets used in previous work were private datasets, making it very difficult to find high quality datasets for this and for other researches. Consequently, researchers often used data augmentation techniques on existing ultrasound images to address the scarcity of publicly available datasets. This reliance on augmented data may introduce variability and bias into the models and affecting the ability of the model to generalize and reliability of the findings. Another significant limitation was due to the edge device used, Raspberry Pi 3 B+ models only have 1GB of RAM, and usually advanced models that can achieve high accuracies are very resource-intensive so even trying to convert the model to TFLite was a challenge as even Kaggle's kernel sometimes failed in converting them due to memory issues.

B. Future Work

Addressing the limitations of this study opens up several paths for future research. Firstly, efforts should be directed towards acquiring or creating more diverse and high-quality datasets for training and evaluation purposes. This would involve collaborating with medical institutions to access larger and more representative datasets that should be made public for researchers. Additionally, exploring alternative edge devices with higher computational capabilities could improve and simplify the process of deploying advanced models for real-world applications. Moreover, investigating techniques to optimize model architecture and employ compression methods could effectively reduce memory and computational constraints, especially in edge device deployment scenarios.

Acknowledgment

I would like to express my sincere gratitude to my advisors, Dr. Shereen Afifi, Prof. Dr. Mohammed Salem, and Eng. Radwa Taha, for their invaluable guidance and assistance throughout this research. Special thanks to my colleagues and friends for their continuous support. Finally, I am deeply grateful to my family for their unwavering love and support.

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