Mini Project Report

on

Breast Tumor Ultrasound Image Segmentation using Deep Learning

By

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Group Id – A03

In partial fulfillment of requirements for the award of degree in

Bachelor of Technology in Computer Science and Engineering

(2023)

Under the Project Guidance of

Bijoyeta Roy

Assistant Professor

Sikkim Manipal Institute of Technology, Majitar

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

SIKKIM MANIPAL INSTITUTE OF TECHNOLOGY

(A constituent college of Sikkim Manipal University)

MAJITAR, RANGPO, EAST SIKKIM – 737136

PROJECT COMPLETION CERTIFICATE

This is to certify that the below mentioned students of Sikkim Manipal Institute of Technology have worked under my supervision and guidance from **9th January 2023 to 29th April 2023** and successfully completed the Mini project entitled **"Breast Tumor Ultrasound Image Segmentation using Deep Learning"** in partial fulfillment of the requirements for the award of Bachelor of Technology in Computer Science and Engineering.

University Registration No	Name of Student	Course
202000382	**Sakshi Saha**	**B.Tech (CSE)**
202000092	**Ishita Sinha**	**B.Tech(CSE)**
202000482	**Raunak Raj**	**B.Tech(CSE)**

Bijoyeta Roy

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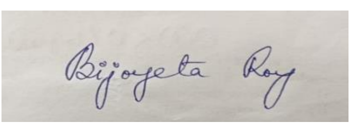
PROJECT REVIEW CERTIFICATE

This is to certify that the work recorded in this project report entitled **“Breast Tumor Ultrasound Image Segmentation using Deep Learning”** has been jointly carried out by **Sakshi Saha (Reg. 202000382), Ishita Sinha (Reg. 202000092) and Raunak Raj (Reg. 202000482)** of Computer Science & Engineering Department of Sikkim Manipal Institute of Technology in partial fulfillment of the requirements for the award of Bachelor of Technology in Computer Science and Engineering. This report has been duly reviewed by the undersigned and recommended for final submission for Mini Project Viva Examination.



Bijoyeta Roy

Assistant Professor

Department of Computer Science and Engineering

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Majhitar, Sikkim – 737136

CERTIFICATE OF ACCEPTANCE

This is to certify that the below mentioned students of Computer Science & Engineering Department of Sikkim Manipal Institute of Technology (SMIT) have worked under the supervision of **Bijoyeta Roy**, Assistant Professor, Department of Computer Science and Engineering from **9th January 2023 to 29th April 2023** on the project entitled **"Breast Tumor Ultrasound Image Segmentation using Deep Learning".**

The project is hereby accepted by the Department of Computer Science & Engineering, SMIT in partial fulfillment of the requirements for the award of Bachelor of Technology in Computer Science and Engineering.

University Registration No	Name of Student	Project Venue
202000382	**Sakshi Saha**	
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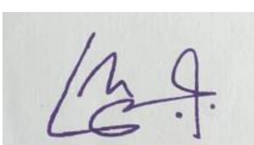
202000482	**Raunak Raj**	



Dr. Udit Kumar Chakraborty

Professor & Head of the Department

Computer Science & Engineering Department

Sikkim Manipal Institute of Technology

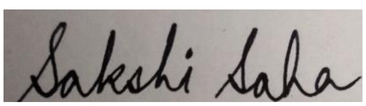
Majhitar, Sikkim – 737136

DECLARATION

We, the undersigned, hereby declare that the work recorded in this project report entitled "**Breast Tumor Ultrasound Image Segmentation using Deep Learning**" in partial fulfillment for the requirements of award of B.Tech (CSE) from Sikkim Manipal Institute of Technology (A constituent college of Sikkim Manipal University) is a faithful and bonafide project work carried out at "**SIKKIM MANIPAL INSTITUTE OF TECHNOLOGY**" under the supervision and guidance of **Bijoyeta Roy,** Assistant Professor, Department of Computer Science and Engineering.

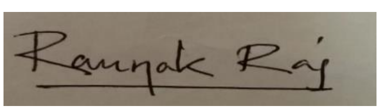
The results of this investigation reported in this project have so far not been reported for any other Degree or any other Technical forum.

The assistance and help received during the course of the investigation have been duly acknowledged.



Sakshi Saha (Reg. No.-202000382)

Ishita Sinha (Reg. No.-202000092)



Raunak Raj (Reg. No.-202000482)

ACKNOWLEDGMENT

We take this opportunity to acknowledge indebtedness and a deep sense of gratitude to our guide **Bijoyeta Roy** for his/her valuable guidance and supervision throughout the course which shaped the present work as it shows.

We pay our deep sense of gratitude to **Prof. (Dr.) Udit Kumar Chakraborty, HOD, Computer Science & Engineering Department, Sikkim Manipal Institute of Technology** for giving us the opportunity to work on this project and providing all support required.

We are obliged to our project coordinators **Dr. Sandeep Gurung** and **Mr. Biraj Upadhyaya** for elevating, inspiration and supervising in completion of our project.

We would also like to thank any other staff of **Computer Science & Engineering Department, Sikkim Manipal Institute of Technology** for giving us continuous support and guidance that has helped us in completion of our project.

Sakshi Saha (Reg. No.-202000382)

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DOCUMENT CONTROL SHEET

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ABSTRACT

This project's goal is to do image segmentation on ultrasound images of breast cancer tumors, “Segmentation is a type of labeling where each pixel in an image is labeled with given concepts.”

It will provide the exact outline of the tumor in the image.

Segmentation involves breaking down an image into distinct and significant parts or areas. In medical image segmentation, the objective is to detect and separate relevant structures or regions of interest in the images, such as tumors, organs, or tissues. This process can be useful in diagnosing, planning treatment, and monitoring the progression of diseases.

1. INTRODUCTION

As mentioned in this research paper , “Breast cancer is one of the primary causes of death among women globally. Early detection and diagnosis can increase the chances of recovery and reduce mortality rates. As per the World Health Organization (WHO), breast cancer was the most frequently diagnosed disease in 2018, with over 2 million new cases reported worldwide. Every year, approximately 626,700 women die from cancer-related diseases”. [https://www.hindawi.com/journals/bmri/2021/9962109/].

Early detection of cancer can significantly lower the mortality rate, reduce treatment costs, and eliminate the need for biopsies. However, radiologists may misdiagnose breast cancer due to the high volume of ultrasound images generated daily, which can overload them.[https://www.hindawi.com/journals/bmri/2021/9962109/].

The probability of successful treatment and a 25.0% reduction in mortality can be increased by identifying and diagnosing breast cancer at an early stage.[https://www.hindawi.com/journals/bmri/2021/9962109/].

While biopsies are the most accurate method for diagnosing breast cancer and pathology results are typically used to confirm the diagnosis, the procedure is resource-intensive and can cause harm to a patient's healthy tissues, leading to physical and emotional discomfort. Consequently, a biopsy may not always be the best option for patient care. [https://www.hindawi.com/journals/bmri/2021/9962109/].

In mammogram analysis, segmentation is used to divide an image into distinct regions to extract the region of interest (ROI) and detect anomalies. However, the presence of pectoral muscles and artefacts in the images can interfere with identification and lead to errors in classification algorithms. Therefore, it is important to eliminate them before segmentation. Various techniques are used to overcome these challenges and accurately extract the ROI from mammogram images.

Image segmentation is a technique used in image processing to partition an image into different segments. In order to accurately identify masses and anomalies in mammograms, it is necessary to remove artefacts and pectoral muscles beforehand. These elements can disrupt the segmentation algorithms and cause misclassification.

LITERATURE SURVEY

SL NO.	AUTHOR	PAPER AND PUBLICATION DETAILS	FINDINGS	RELEVANCE TO THE PROJECT
1.	Epimack Michael, He Ma, Hong Li, Frank Kulwa, and Jing Li	Breast Cancer Segmentation Methods – Current Status and Future Potential Published on 22nd July 2021 Published at Hindawi Journal: BioMed Research International	• Region-based segmentation is a classical approach that is commonly used in image processing. The most popular technique for this is region expanding. • Traditional segmentation methods commonly use the MIAS database and median filter. • For medical image data, the most commonly used methods in deep learning are U-Net and unsupervised machine learning. They are advantageous because they were specifically designed for medical images and do not require a large number of annotated photos.	• The picture segmentation pipeline was introduced. • Cutting-edge methods for image segmentation were thoroughly examined. • Discussed the frequently used filters for image noise reduction, publicly and privately available image databases for segmentation metrics and classification, as well as the most popular techniques for classical, machine learning, and deep learning-based segmentation.

2.	Aleksander Vakanski, Min Xian, Phoebe E. Freer	Attention enriched deep learning model for breast tumor segmentation in ultrasound images Published on 20th July 2020 Published at PubMed Central Journal: Ultrasound Med Biol	• The proposed model is a variation of the U-Net, which incorporates attention blocks into the encoder layers during the contracting path. • The integration of attention blocks into the deep learning model allows it to selectively focus on regions with high saliency values while disregarding areas with low saliency values. These blocks utilize saliency maps at multiple scales. • While the vanishing gradient problem was addressed by integrating Res Path into U-Net, it also resulted in inaccuracies in the segmentation output.	• A method, named RCU-Net, was suggested for the segmentation of breast tumors in ultrasound images, which is based on the U-Net structure. • The integration of attention blocks within the encoder layers enables the neural network to acquire feature representations that prioritize regions with significant saliency values, directing its spatial attention towards the target areas.

3.	Kailuo Yu, Sheng Chen, Yanghuai Chen	Tumor segmentation in breast ultrasound image by means of Res Path combined with dense connection neural network Published on 28th August 2021 Published at PubMed Central Journal: Diagnostics	• To minimize the semantic gap between the encoder and decoder and solve this issue, a novel link consisting of dense blocks can be used.	• A proposed approach involved establishing a Residual Path that connects the encoder to the decoder, in addition to creating a novel connection between the input and decoder. • Implementation of the Residual Path in the U-Net architecture facilitated the mitigation of inconsistencies in feature maps between the encoder on the left-hand side and the decoder on the right-hand side. • Moreover, the introduced connection has the potential to expedite the rate of convergence of the model, augment its capability to extract features, and diminish the extent of overfitting.

4.	Yaozhong Luo, Qinghua Huang, Xuelong Li	Segmentation Information with attention integration for classification for breast tumor in ultrasound image Published on 11th November 2021 Journal: ScienceDirect	• Breast classification involves extracting features solely from ultrasound images of the breast. • To integrate medical expertise into the network, a segmentation network was developed to obtain the tumor region and contour for extracting more efficient features.	• A distinctive architecture designed to enhance tumor segmentation and extract clinical diagnostic information more efficiently. • Unlike the conventional DCNN architecture, the system includes a parallel branch for feature extraction. • The segmentation network generates a segmentation outcome that is subsequently fed into the convolution network for feature extraction. • The segmentation network generates a segmentation outcome that is subsequently fed into the convolution network for feature extraction.

5.	Naresh Khuriwal, Nidhi Mishra	Breast Cancer Detection From Histopathological Images Using Deep Learning Published on 9th May 2019 Published at IEEE Xplore Journal: IEEE	• A CNN was employed as a DL technique. • The model achieved an accuracy of 98% • The model was trained and tested using only 12 features.	• The MIAS dataset was analyzed using the Deep Learning Neural Network Algorithm. • Compared to other segmentation methods, the watershed transform technique performs better as it can accurately identify and differentiate between foreground and background areas.
6.	Diyar Qader Zeebaree, Habibollah Haron, Adnan Mohsin Abdulazeez, Dilovan Asaad Zebari	Machine Learning and Region Growing for Breast Cancer Segmentation Published on 30th May 2019 Published at IEEE Xplore Journal: IEEE	• One of the challenges arises due to the overlapping of a cyst with the background issues and variations in color intensities. • The segmentation framework employs trainable segmentation as the first step to identify tumor regions, followed by post-segmentation methods such as	• The main contribution of the study is the creation of a self-learning model that can accurately segment and identify abnormalities related to breast cancer, known as computer-aided diagnosis (CAD). • A machine learning based trainable model was developed to tackle the challenge of extracting ROI from images during the method's development. • Aiming to improve the detection of the region of interest (ROI) from the background, a new proposed model based on multi-descriptor (texture

				distance transform and region expanding to achieve accurate segmentation.	feature) was developed to provide an efficient solution for ROI extraction from images.

Table 1.1: Literature Survey

PROBLEM DEFINITION

1. The outcomes of traditional machine learning techniques in image processing were imprecise and insufficient.[*https://www.hindawi.com/journals/bmri/2021/9962109/*]

2. The challenge is to determine the depth of an object from a single image.

3. Image processing tasks include "Image Filtering," "Image Restoration," "Image Registration," "Image Fusion," "Image Segmentation," and "Image Classification."

4. Breast cancer patients may be misdiagnosed by clinicians based on ultrasound images due to the variation in tumor appearance.

5. **An automated model for tumor segmentation in ultrasound images can be developed using deep learning techniques to enhance accuracy.**

SOLUTION STRATEGY

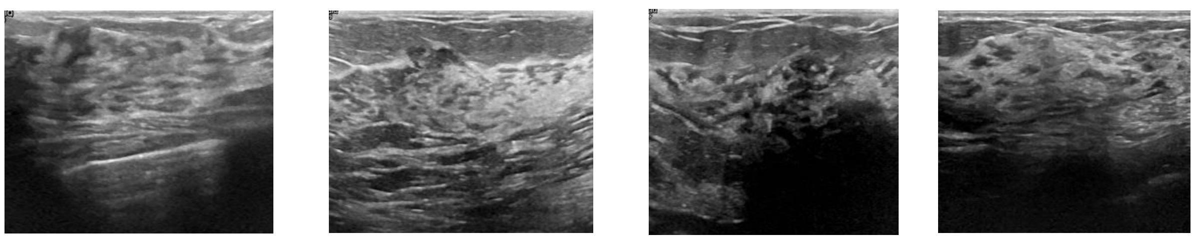
1. One can leverage deep learning in the domain of image processing to generate accurate and precise outcomes.
2. The aim is to develop an Attention U-Net deep learning model that can accurately segment tumor regions in a sequence of breast ultrasound images. The model takes an ultrasound image as input and produces a binary mask that highlights the location of the tumor in the image.
3. The ultimate goal is to create a picture segmentation model with high accuracy and efficiency that can assist medical professionals in detecting and managing breast cancer at an early stage.

DATASETS

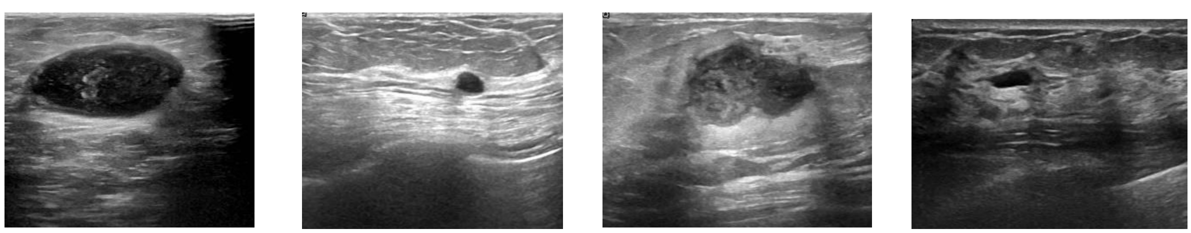
- Breast cancer is a significant cause of death for women worldwide.
- Early detection can help reduce premature mortality.
- Medical images of breast cancer were gathered through ultrasound scans.
- The Breast Ultrasound Dataset has three categories: normal, benign, and malignant.
- Images were collected from 600 female patients aged 25 to 75 in 2018.
- The dataset contains 780 500x500 pixel PNG images.
- Both original and ground truth images are included in the dataset.

[https://www.kaggle.com/code/utkarshsaxenadn/breast-cancer-image-segmentation-attention-unet].

Normal :-



Benign :-



Malignant :-

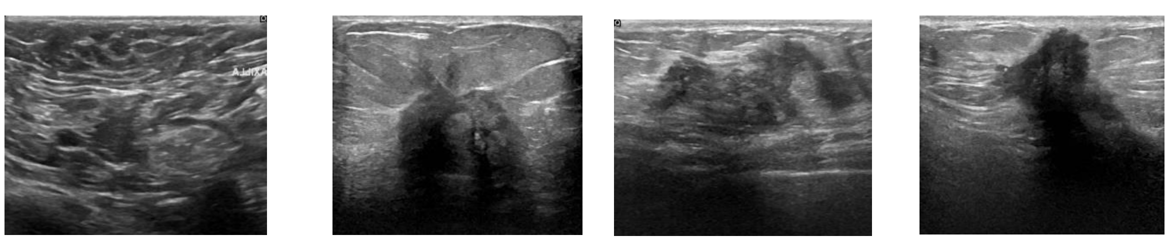


Fig 1.1: Datasets
[https://www.kaggle.com/code/utkarshsaxenadn/breast-cancer-image-segmentation-attention-unet]

U-NET ARCHITECTURE

The Attention U-Net Model is a well-known approach for multi-class segmentation of breast tumor ultrasound images. It comprises three main components: Encoder Block, Decoder Block, and Attention Gate. The Encoder Block, located on the left side of the U-Net, consists of two iterative "3x3 convolutions" followed by "ReLU" and batch normalization, which reduces spatial dimensions using "2x2 max pooling." In the Decoder Block, the feature map is upsampled and concatenated with the corresponding Encoder Block feature map, halving the number of feature channels. The top layer uses a 1x1 convolution to map channels to the desired number of classes. The Attention Gate ensures the model's focus is directed to relevant regions while suppressing activations in unrelated areas, resulting in a lightweight and computationally efficient model. The objective is to enhance segmentation accuracy in breast tumor ultrasound images, which can aid in early detection and management of breast cancer by medical professionals.

The U-Net model uses a "downsampling" step to increase the number of feature channels and reduce spatial dimensions, followed by an "upsampling" step to decrease the number of feature channels and increase spatial dimensions. The attention gate helps focus the model on important regions while suppressing features in irrelevant areas. The model is lightweight and doesn't require a large number of parameters.

ATTENTION U-NET :-

What is U-Net?

U-Net is commonly used for image segmentation tasks in biological images, but it also works for segmenting photos from the natural world. However, gathering annotated medical images for training is expensive, and thousands of annotated training samples are needed for successful deep learning model training. U-Net can still produce accurate segmentation results with fewer training samples, which is important for medical images where small segmentation errors can have significant clinical consequences.

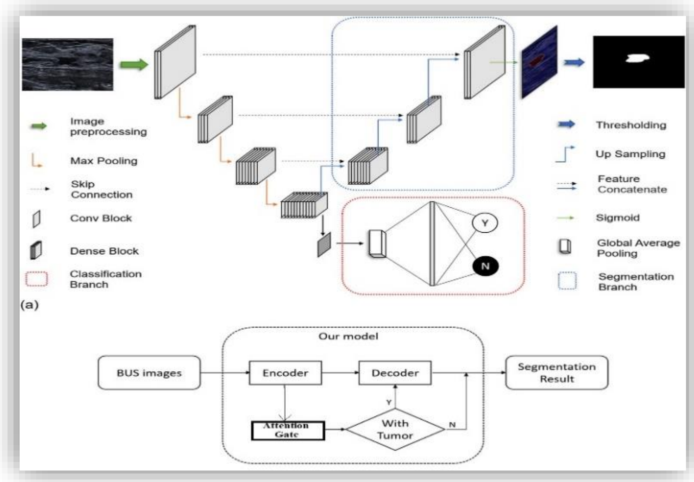
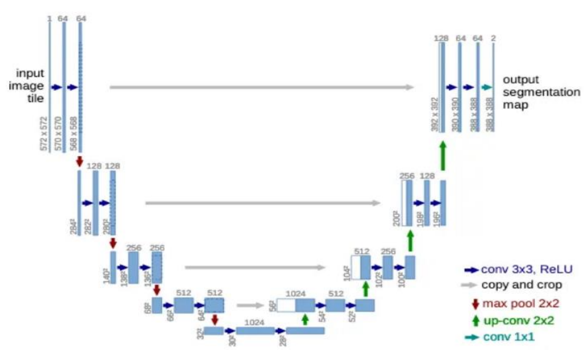


Fig 1.2: Basic U-Net Architecture
[https://towardsdatascience.com/a-detailed-explanation-of-the-attention-u-net-b371a5590831]

What is attention?

Attention is a technique used in image segmentation to highlight important activations during training, improving the network's ability to generalize. Hard attention crops the image or iteratively selects regions, while soft attention weights different aspects of the image. Relevant areas receive higher weights, while less relevant areas receive lower weights.

Why is attention needed in the U-Net?



Grey arrows denote the long skip connections used in the U-Net. (Ronneberger et al., 2015)

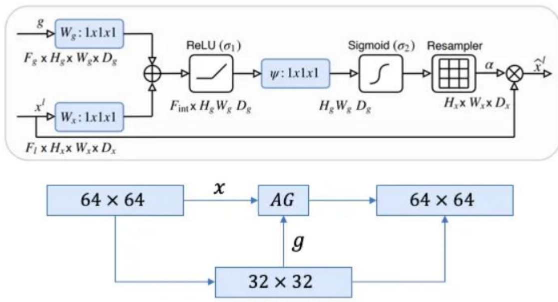
Fig 1.3: Attention U-Net Model

[https://towardsdatascience.com/a-detailed-explanation-of-the-attention-u-net-b371a5590831]

To improve the spatial information in the upsampling path of U-Net, skip connections are used to combine it with the downsampling path. However, this leads to redundant low-level feature extractions. Soft attention is used at the skip connections to reduce the transfer of redundant features by suppressing activations in unnecessary regions.

How is attention implemented?

a) Breakdown of attention gates



Top: Attention gate (AG) schematic. Bottom: How AGs are implemented at every skip connection.

Fig 1.4: Attention U-Net Implementation
[https://towardsdatascience.com/a-detailed-explanation-of-the-attention-u-net-b371a5590831]

IMPLEMENTATION DETAILS

Algorithm :-

1. Start
2. Import necessary libraries (numpy, pandas, matplotlib, tensorflow, keras).
3. Set the parameters for reading the datasets.
4. Read the datasets (N number of layers).
6. Create an instance of Attention U-Net with encoding and decoding layers, attention gates and skip connections.
7. Train the Attention U-Net model on a dataset of breast tumor ultrasound images with corresponding ground truth segmentation masks.
8. Perform segmentation on the datasets using Attention U-Net model.
9. Return the segmented image with tumor region highlighted.
10. Stop

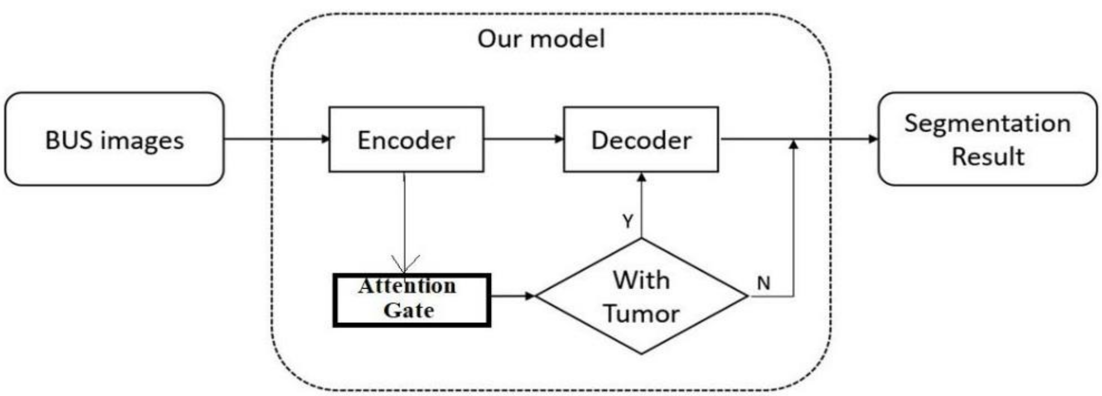


Fig 1.5: Simplest Representation of the Model

DESIGN ARCHITECTURE OF PROPOSED MODEL

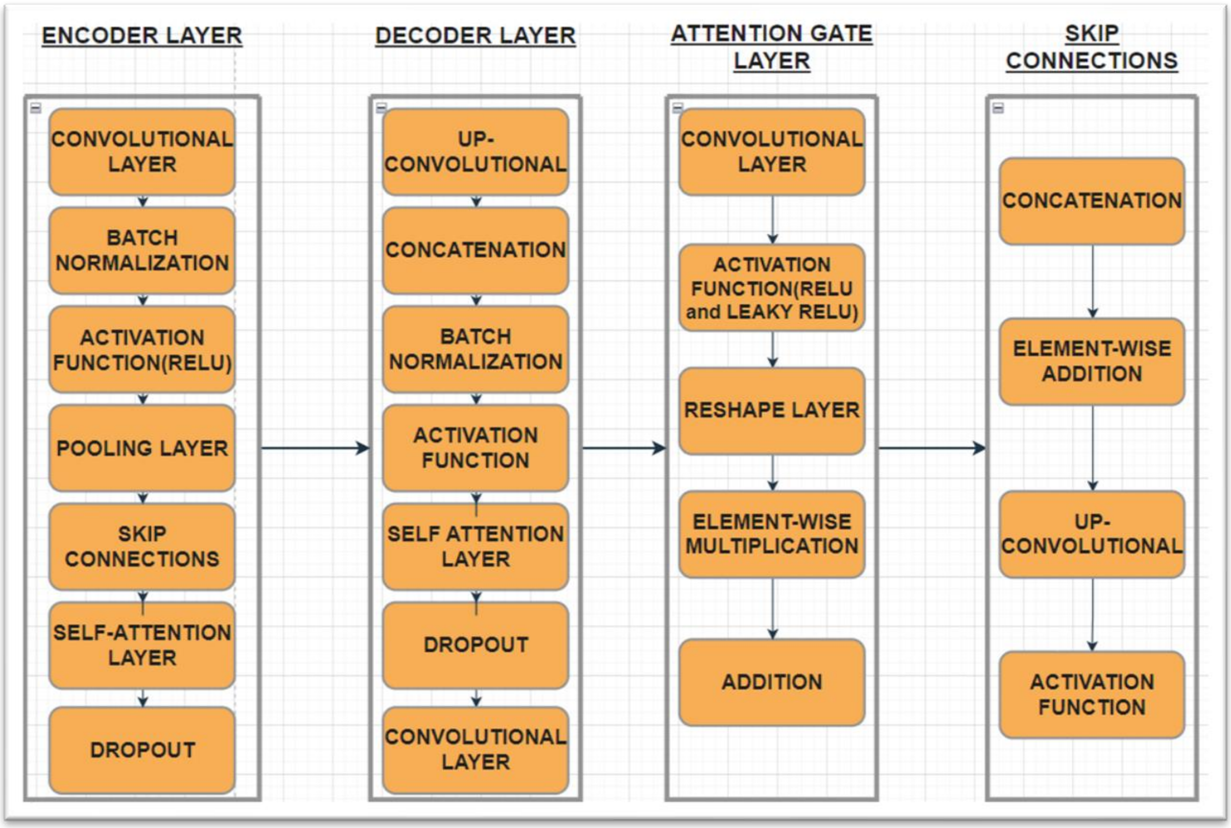


Fig 1.6 Layered Diagram of Proposed Model

PSEUDOCODE

Encoder:

```
def encoder_block(input, num_filters):
   # Convolutional Layers
   x = Conv2D(num_filters, kernel_size=3, padding='same',
kernel_initializer='he_normal')(input)
   x = BatchNormalization()(x)
   x = Activation('relu')(x)
   x = Conv2D(num_filters, kernel_size=3, padding='same', kernel_initializer='he_normal')(x)
   x = BatchNormalization()(x)
   x = Activation('relu')(x)

   # Max Pooling Layer
   pool = MaxPooling2D(pool_size=(2, 2))(x)

   return pool, x
```

Decoder:

```
def decoder_block(input, skip_features, num_filters):
   # Upconvolutional Layer
   x = UpSampling2D(size=(2, 2))(input)
   x = Concatenate()([x, skip_features])

   # Convolutional Layers
   x = Conv2D(num_filters, kernel_size=3, padding='same', kernel_initializer='he_normal')(x)
   x = BatchNormalization()(x)
   x = Activation('relu')(x)
   x = Conv2D(num_filters, kernel_size=3, padding='same', kernel_initializer='he_normal')(x)
   x = BatchNormalization()(x)
   x = Activation('relu')(x)

   return x
```

Attention Gate:

```
def attention_gate(input_x, input_g, num_filters):
   g1 = Conv2D(num_filters, kernel_size=1, kernel_initializer='he_normal')(input_g)
   x1 = Conv2D(num_filters, kernel_size=1, kernel_initializer='he_normal')(input_x)
   psi = Activation('relu')(add([g1, x1]))
   psi = Conv2D(1, kernel_size=1, kernel_initializer='he_normal')(psi)
   psi = Activation('sigmoid')(psi
   x = Multiply()([input_x, psi])

   return x
```

FLOWCHART

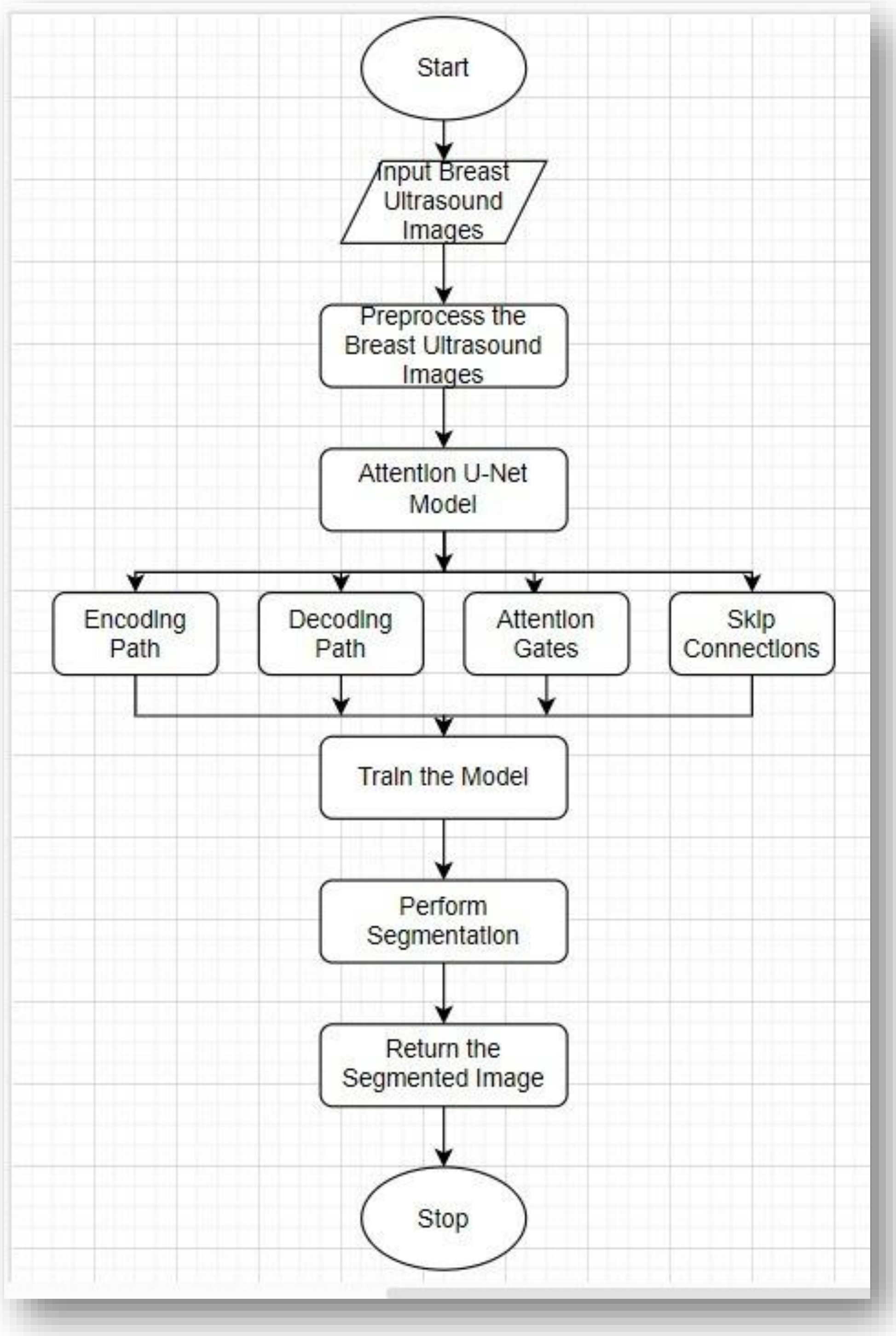


Fig 1.7: Flowchart

RESULTS

Preprocessing the Dataset :

Fig 1.8: Preprocessed Datasets

Training the Model using Sigmoid Activation Function :

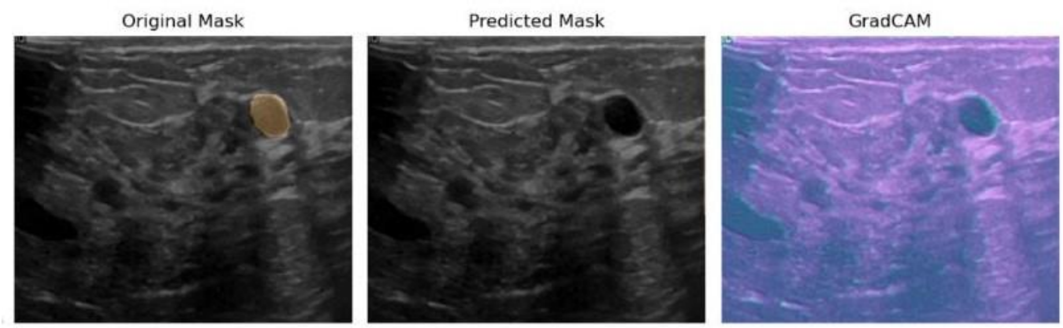


Fig 1.9: Training the model using sigmoid activation function

Table of Performance Metrics for the Model: Loss, Accuracy, and Intersection over Union (IoU):

Loss	Accuracy	IoU	Validation Loss	Validation Accuracy	Validation IoU
13991.328125	0.874591	0.454643	9353.539062	0.981338	0.490923
33457.496094	0.809476	0.431045	7.508394	0.971747	0.487909
43.880058	0.817023	0.441178	3.578994	0.977896	0.489358
19.826937	0.821833	0.450824	3.826360	0.975658	0.489995
11.969678	0.822708	0.456429	8.412814	0.979034	0.490039
9.720598	0.837377	0.463246	35.892620	0.978472	0.489630
8.224049	0.835015	0.466950	20.213385	0.977920	0.489475
4.231709	0.849548	0.474443	14.674939	0.976545	0.488986
3.106967	0.854600	0.474999	11.370493	0.928288	0.496350
2.284303	0.859092	0.471662	13.217771	0.893668	0.492134
6.204035	0.856352	0.467412	20.608765	0.978595	0.489677
9.946469	0.838452	0.463724	11.236804	0.976255	0.488608
4.010652	0.851487	0.471944	8.167299	0.972416	0.489353

Table 1.2: Performance Metrics using sigmoid activation function

Graph showing model loss, model accuracy and model IoU:

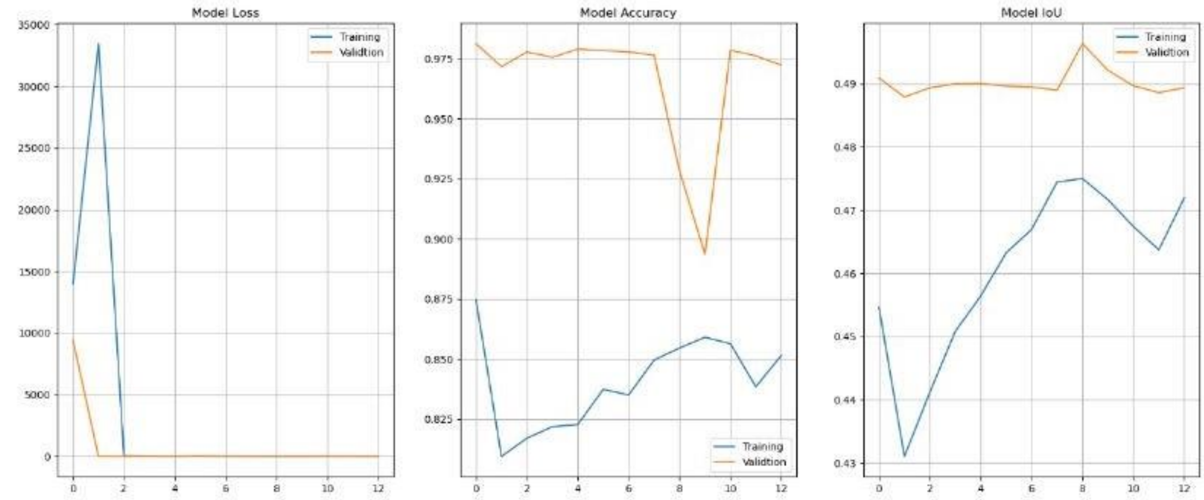


Fig 1.10: Graph obtained using sigmoid activation function

Images Obtained After Training using Sigmoid Activation Function:

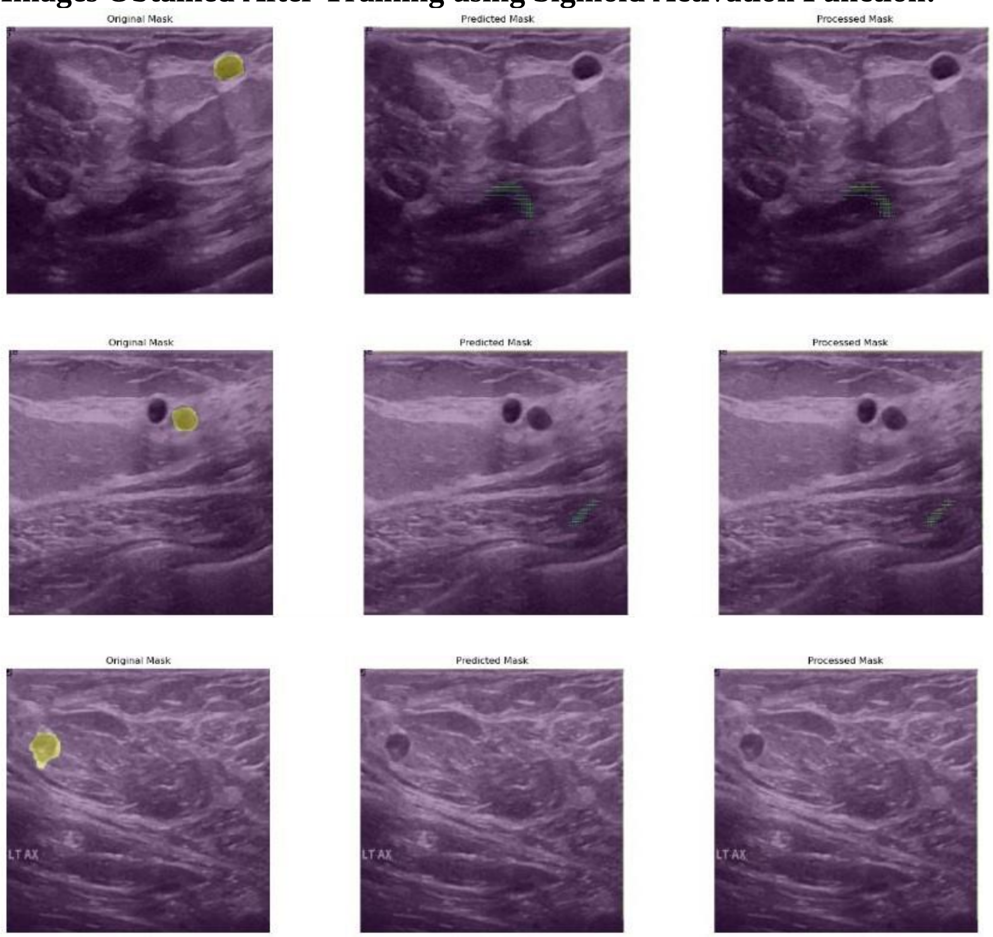


Fig 1.11: Images obtained using sigmoid activation function

Training the Model using ReLu Activation Function:

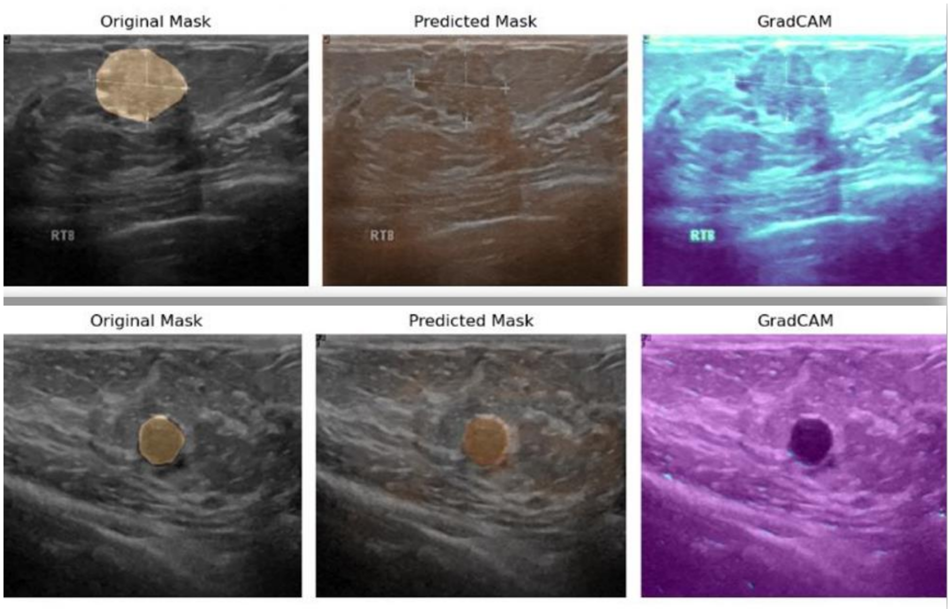


Fig 1.12: Training the model using ReLu activation function

Table of Performance Metrics for the Model: Loss, Accuracy, and Intersection over Union (IoU):

	Loss	Accuracy	IoU	Validation Loss	Validation Accuracy	Validation IoU
0	0.314331	0.906615	0.454950	0.138468	0.981338	0.490924
1	0.275230	0.905493	0.453982	0.089808	0.981100	0.490924
2	0.253149	0.906989	0.454400	0.115896	0.979271	0.490924
3	0.233634	0.910658	0.455527	0.085127	0.981323	0.490924
4	0.225836	0.917000	0.455249	0.081508	0.981521	0.490924
5	0.216988	0.918484	0.455242	0.087053	0.979917	0.491025
6	0.214481	0.920206	0.454902	0.086504	0.979652	0.491192
7	0.204267	0.923748	0.455589	0.309678	0.880135	0.491031
8	0.200470	0.925517	0.455458	0.117717	0.964655	0.491000
9	0.196940	0.928688	0.456274	0.110432	0.978759	0.490924
10	0.188342	0.929150	0.455305	0.095442	0.978780	0.491013
11	0.185932	0.928873	0.457694	0.121150	0.971402	0.491170
12	0.189714	0.929078	0.454898	0.103378	0.979821	0.491128
13	0.164891	0.939800	0.458523	0.179740	0.922079	0.490924
14	0.187977	0.931231	0.454483	0.146762	0.960422	0.490924
15	0.174999	0.934753	0.456104	0.092686	0.975963	0.491075
16	0.000000	0.000000	0.000000	0.092686	0.975963	0.491075

Table 1.3: Performance Metrics using ReLu activation function

Graph showing model loss, model accuracy and model IoU:

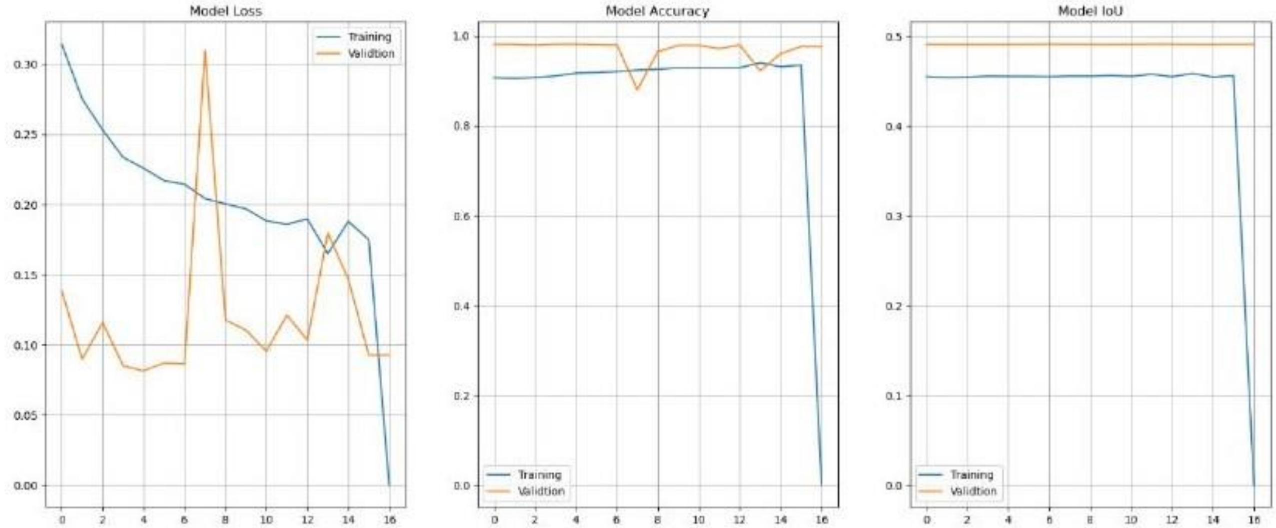


Fig 1.13: Graph obtained using ReLu activation function

Images Obtained after Training using ReLu Activation Function:

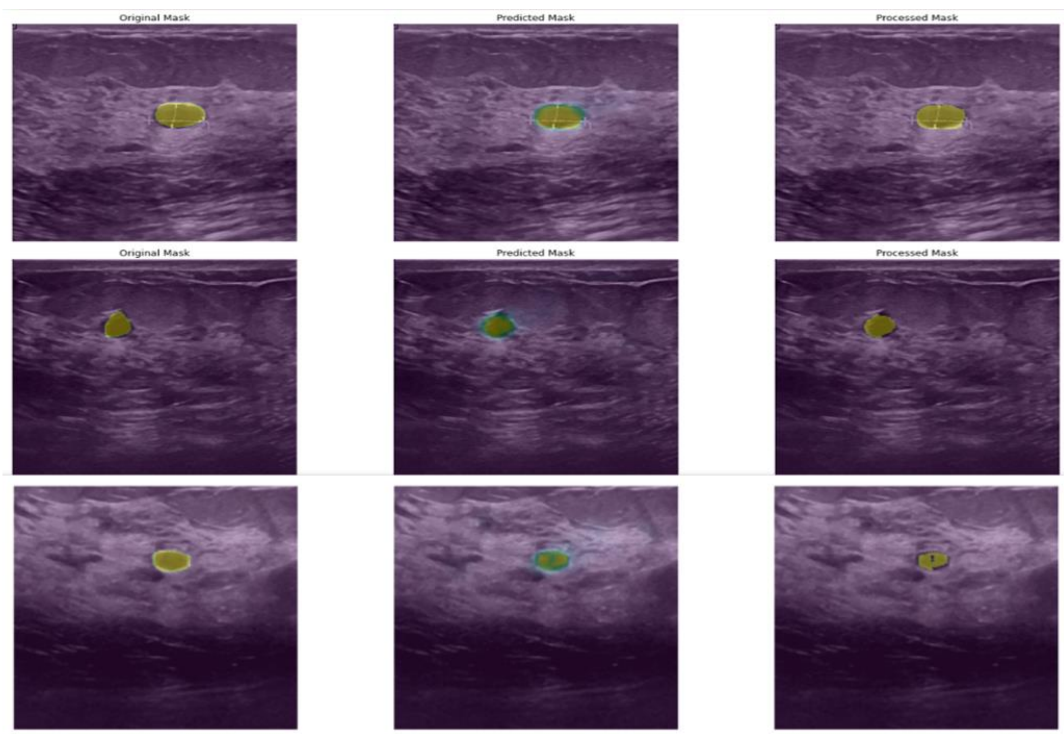


Fig 1.14: Images obtained using ReLu activation function

Training the Model using Leaky ReLu Activaion Function:

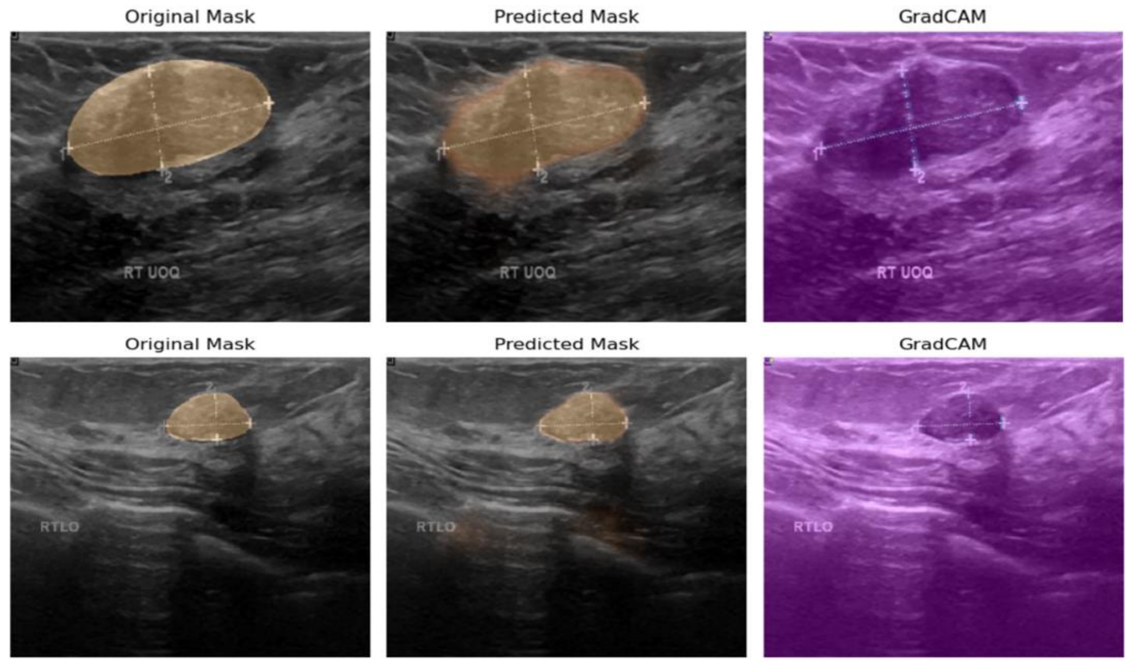


Fig 1.15: Training the model using Leaky ReLu activation function

Table of Performance Metrics for the Model: Loss, Accuracy, and Intersection over Union (IoU):

	Loss	Accuracy	IoU	Validation Loss	Validation Accuracy	Validation IoU
0	0.176653	0.936246	0.455780	0.065330	0.982142	0.490924
1	0.156790	0.942375	0.458669	0.068086	0.983484	0.490924
2	0.173708	0.935843	0.455384	0.072062	0.980820	0.491026
3	0.166744	0.939375	0.459122	0.080075	0.980547	0.490899
4	0.154963	0.944100	0.461899	0.076790	0.978837	0.490949
5	0.143621	0.947371	0.463682	0.067006	0.981857	0.490924
6	0.149815	0.945122	0.459750	0.059593	0.984610	0.490926
7	0.139261	0.947389	0.457792	0.083704	0.974625	0.491131
8	0.132372	0.950610	0.466290	0.100629	0.965493	0.491108
9	0.170683	0.940298	0.460834	0.094203	0.979597	0.492519
10	0.156854	0.942051	0.461611	0.069663	0.982072	0.491014
11	0.142266	0.947257	0.464238	0.092822	0.971308	0.490970
12	0.132430	0.951475	0.461474	0.074045	0.976799	0.490980

Table 1.4: Performance Metrics using Leaky ReLu activation function

Graph showing model loss, model accuracy and model IoU:

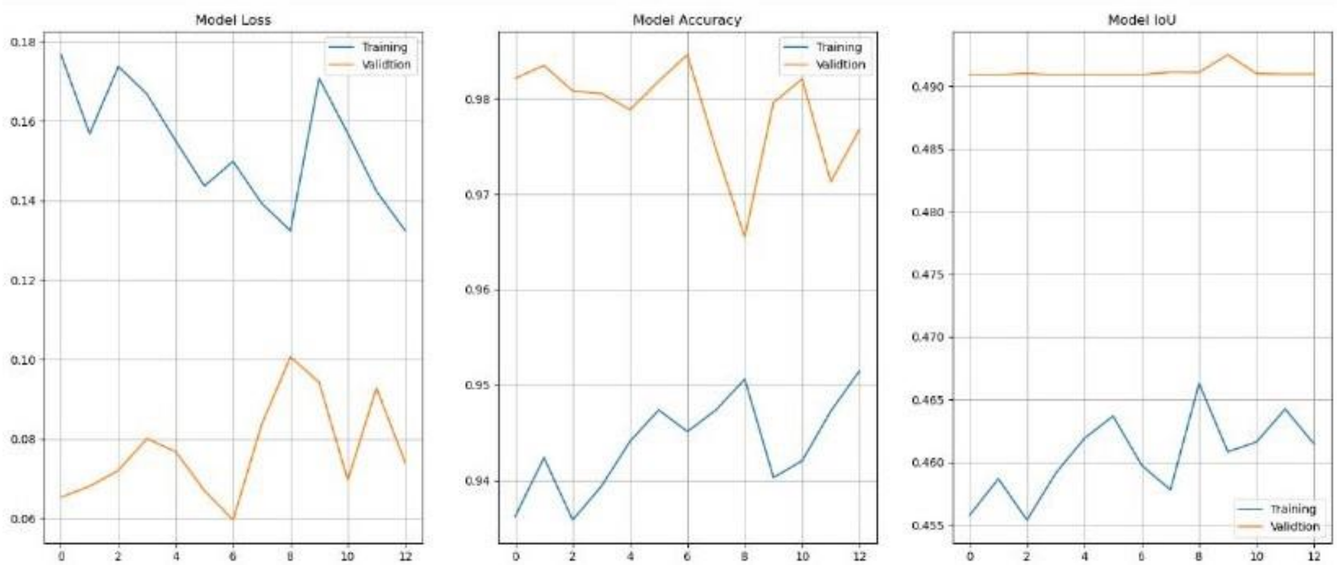


Fig 1.16: Graph obtained using Leaky ReLu activation function

Images Obtained after Training using Leaky ReLu Activation Function:

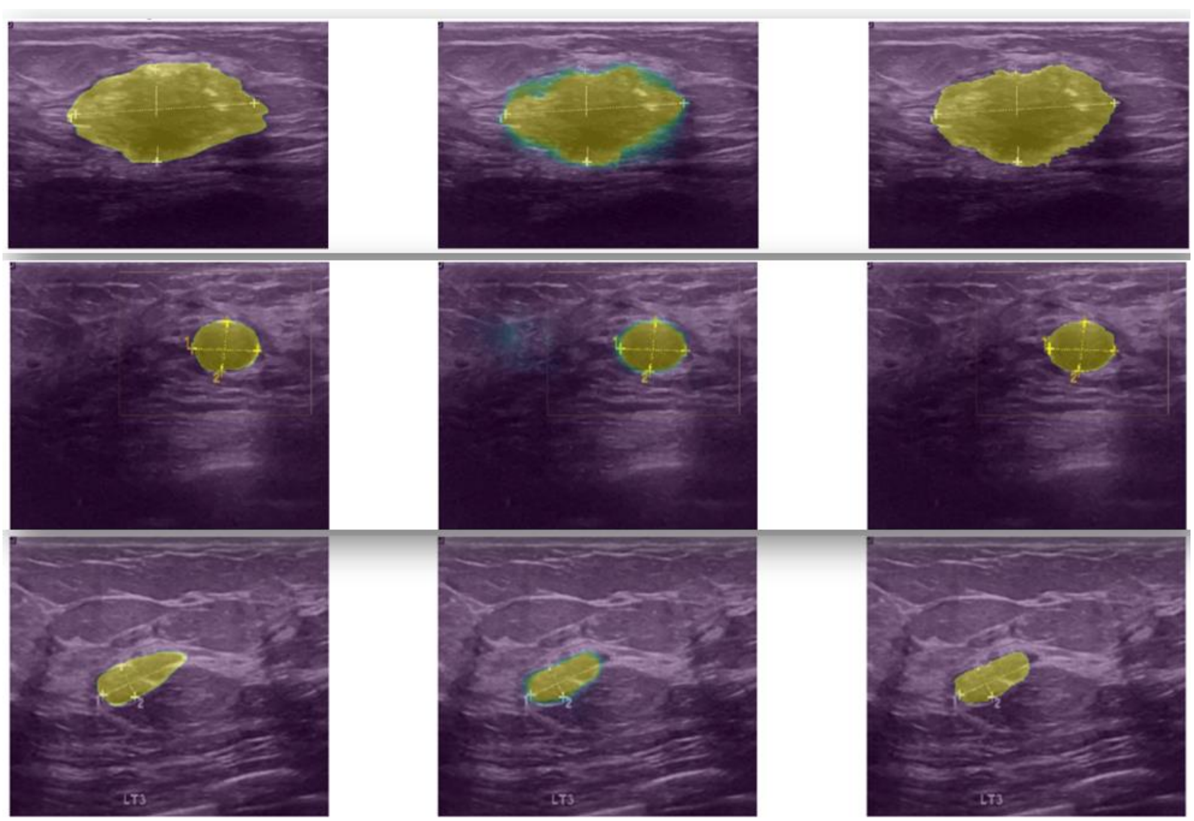


Fig 1.17: Images obtained using Leaky ReLu activation function

Comparison of Results Based on Activation Function:

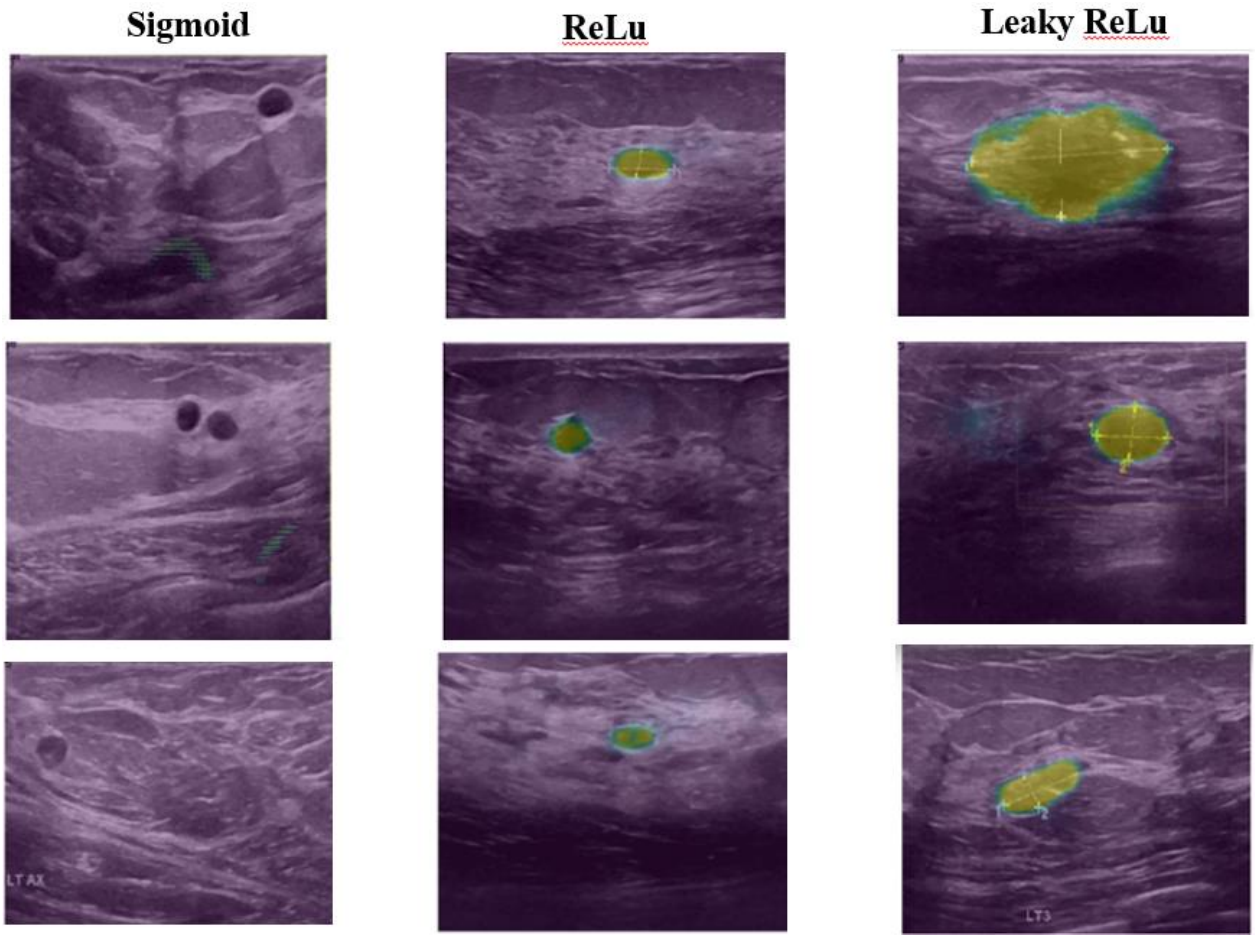


Fig 1.18: Comparison of the results

The model is trained on images and masks with a batch size of 8 and for 12 epochs using Sigmoid, ReLu, and Leaky ReLu activation functions. It evaluates performance using 20% validation split and mean intersection over union measure. Callbacks like ModelCheckpoint and ShowProgress are used to save model weights and display original and predicted masks with GradCAM visualisation for a random image after each epoch.

FUTURE SCOPE AND LIMITATIONS

Future Scope:

U-Net has showed considerable promise in terms of reaching high accuracy in breast tumour segmentation. However, in terms of segmentation accuracy, there is always potential for improvement, particularly for small or overlapping tumours. Future research could concentrate on building more advanced attention mechanisms that can better catch tumour traits and increase segmentation accuracy.

Limitations:

- U-Net can be susceptible to noise in the input data, resulting in segmentation mistakes.
- U-net can be sensitive to variations in picture quality, contrast, and brightness, resulting in segmentation problems.

CONCLUSION

We performed image segmentation on breast tumor ultrasound images using attention U-Net using three different activation functions namely Sigmoid(**85%**), ReLu(**93%**) and Leaky ReLu(**95%**). Leaky ReLu has been found to be more accurate due to the fact that Leaky ReLu function solves the “dying ReLu” problem and provides a non-zero gradient for negative inputs resulting in the better optimization of the model. Additionally, Leaky ReLu is computationally more efficient and easy to implement.

According to recent studies published in Medical Image Analysis and IEEE Access, an attention U-Net model performed well in segmenting breast tumor ultrasound images. The average Dice scores obtained from the two studies were in the range of 0.89-0.896, indicating state-of-the-art accuracy.

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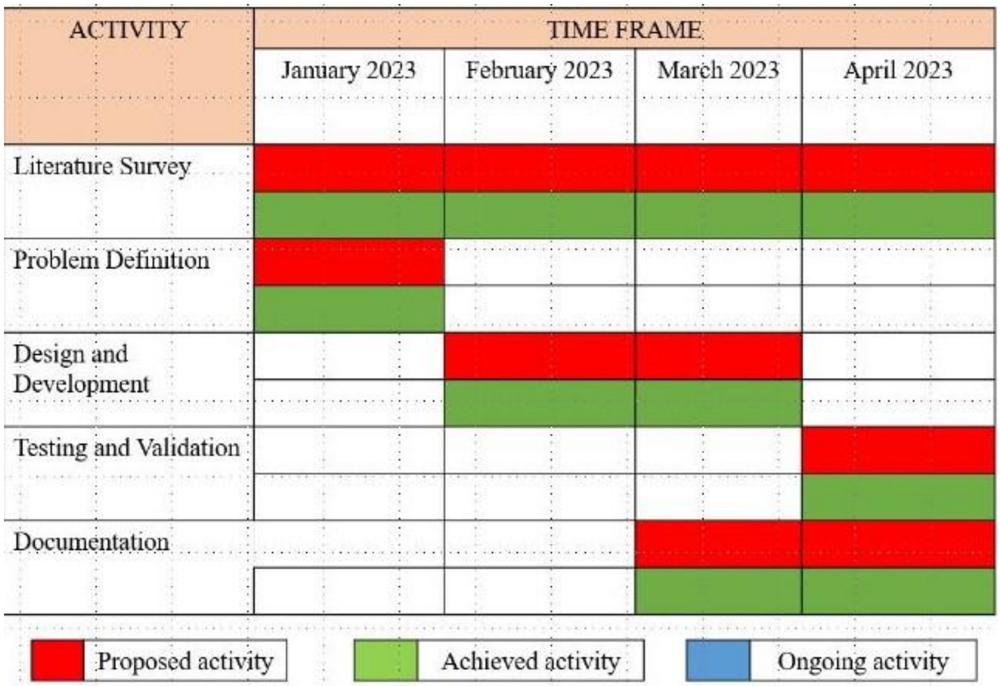
ACTIVITY
TIME FRAME
January 2023
February 2023
March 2023
April 2023
Literature Survey
Problem Definition
Design and Development
Testing and Validation
Documentation
Proposed activity
Achieved activity
Ongoing activity

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THANKYOU