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Shima Baniadam Dizaj ( baniadam.shima@gmail.com )
Pourya Valizadeh

Research Article

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# Breast cancer segmentation and classification in ultrasound images using convolutional neural network

Shima Baniadam Dizaj
Department of electrical and computer engineering
Kharazmi University
Tehran, Iran
baniadam.shima@gmail.com

Pourya Valizadeh
Department of electrical and computer engineering
Kharazmi University
Tehran, Iran
pourya.valizadeh@gmail.com

*Abstract*— **Breast most cancers is one of the main reasons of mortality in ladies throughout the world. Early detection contributes to a discount withinside the quantity of untimely fatalities. Using ultrasound (US) pics, we gift deep studying (DL) strategies for breast most cancers segmentation and category into 3 classes: regular, benign, and malignant. The versions in most cancers length and traits are the mission of segmentation and category tasks. The proposed technique became evolved and evaluated the use of US pics amassed from 780 breast cancers. This has a look at tested using deep studying to scientific pics of breast most cancers acquired with the aid of using ultrasound scan. For evaluation, we used intersection over union (IoU), accuracy. When evaluated with IoU the nice proposed technique yielded 100%curacy on regular breast segmentation, 79.27% on benign, and 93.73% on malignant most cancers. Also, the accuracy of category three classes is 87.86%. Our have a look at indicates the usefulness of deep studying techniques for breast most cancers segmentation and category. You can locate the pre-skilled weights and elements of our Implementation and the prediction of our technique may be located at https://github.com/shb8086/Cancer.**

***Keywords—Breast cancer, Convolutional neural networks, Ultrasound imaging, Deep learning***

## I. Introduction

Ultrasound (US) is a beneficial manner for the detection and prognosis of various styles of most cancers like breast most cancers [1] due to the fact they're non-radioactive, non-invasive, real-time imaging and high-decision photograph, particularly accessible, and inexpensive. At the identical time studying US pics calls for well-skilled and professional radiologists and great understanding of function photograph functions proven to be associated with benign or malignant breast most cancers. Even a skilled professional may have a mistake at the tumor's kind prognosis [2]. Breast most cancers is the maximum not unusual place invasive most cancers in girls and US imaging has been broadly used for most cancers' evaluation. Hence, laptop-aided prognosis (CAD) might be used to useful resource radiologists in breast tumor category and detection [3-5]. Mass segmentation is a vital step withinside the CAD machine to correct segmentation. Some articles have mentioned the automation of breast most cancers to categories benign and malignant most cancers in US pics.

Recently deep mastering (DL) algorithms are displaying properly effects for breast photograph analysis. These powerful data-pushed strategies manner enter pics to study high-stage photograph illustration decisions [6-8]. Convolutional neural networks (CNNs) had been efficaciously carried out and established to be very powerful in laptop imaginative and prescient packages for the detection, category, and segmentation of breast most cancers in US pics [9-20]. Also, CNN can apprehend visible styles immediately from pixel pics with minimum preprocessing and automate the entire function extraction manner. Recently, using CNN fashions in ultrasound of breast most cancers is proven tremendous development.

In this take a look at, we offered a singular utilization of 5 exclusive CNN fashions for breast most cancers segmentation and category in US pics. The nice end result is for U-Net. U-Net is the maximum famous CNN for semantic item segmentation [22-23]. Standard U-Net structure includes contracting and increasing paths. First, withinside the encoder part (contracting) enter photograph is processed the usage of convolutional and pooling operators to supply a compressed photograph illustration. Second, withinside the decoder phase (expansion), the representations is upsampled with convolutional operators to create the segmentation masks displaying item position. Also, bypass connections are used to propagate function maps from the contraction to expiation path [24]. Although, popular U-Net makes use of convolutions of the constant receptive field. The segmentation technique proposed on this take a look at is primarily based totally on U-Net's cap potential to reconstruct the photograph. We will deliver the version a few photographs as functions and their corresponding masks pics as labels. Because of the reconstructive functions of the U-Net, the U-Net can generate pics as output. Here we're the usage of a supervised mastering approach.

## II. Related Works

In this section, we introduce and speak distinctive papers labored on breast most cancers category, segmentation, and detection. Antropova et al. [9] verified a way for extracting and pooling low- to mid-stage capabilities making use of a pre-skilled convolutional neural community with conventional CAD processes. Across 3 scientific imaging modalities, our fusion-primarily based totally method outperforms previous breast most cancers CAD algorithms. Moon et al. [15] proposed a CAD machine for tumor prognosis the usage of a photo fusion technique blended with distinctive photo content material representations and ensemble distinctive CNN architectures on US pix.

Yap et al. [18] proposes using deep gaining knowledge of algorithms for breast US lesion identity and explores 3 techniques: a Patch-primarily based totally LeNet, a U-Net, and a switch gaining knowledge of method with a pre-skilled FCN-AlexNet. Furthermore, this newsletter analyzes and contrasts conventional ultrasound image datasets received from awesome ultrasound structures. Rests traditional ultrasound photo datasets obtained from distinctive ultrasound structures. Yala et al. [19] confirmed a deep gaining knowledge of version that immediately makes use of full-area mammograms. These effects help the speculation that mammograms include informative chance signs now no longer captured through conventional chance factors, and DL fashions can infer those styles from the information. These fashions have the capability to update traditional chance, prediction fashions.

Byra et al. [13] proposed a satiation conversion technique that transfers the grayscale ultrasound pix to 3-channel (RGB) pix and improved the category overall performance. Yap et al. [10] additionally, proposed an cease-to-cease deep gaining knowledge of version in computerized breast ultrasound lesions reputation in some other paper. They applied the primary semantic segmentation on BUS pix and in comparison, the overall performance among distinctive CNN fashions. Yap et al. [21] proposed an automated detection machine of breast ultrasound lesions the usage of CNN fashions, which in comparison 3 distinctive CNN fashions of CAD structures and decreased the operator relying at the problem. Han et al. [11] proposed a semi-supervised method to the improvement of segmentation networks. They guided a completely convolutional neural community with generative opposed networks.

Drukker et al. [25] investigated using a radial gradient index (RGI) filtering method to mechanically stumble on lesions on breast ultrasound pix. Then, lesion applicants had been segmented from the blackboard through maximizing a median radial-gradient (ARD) index for areas grown from the detected points. Next, sound robin evaluation become used to get entry to the high-satisfactory of the category of lesion applicants into real lesions and fake positives through a Bayesian neural community. And it suggests that the usage of automatic evaluation helps using breast most cancers detection in sonography pix.

Overall, without having sturdy assumption, deep gaining knowledge of processes have proven suitable accuracy in item detection, segmentation, and category which shows that would additionally enhance the kingdom of the artwork of lesion detection in breast ultrasound. Deep gaining knowledge of in clinical imaging is normally represented through convolutional networks. Some of the deep gaining knowledge of-primarily based totally processes used Patch-primarily based totally CNNs. This method trains the convolutional neural networks (CNNs) with photo patches for education and a sliding window method for testing [26,27]. Furthermore, feeding each patch into the community takes a few times, and patch overlap effects in substantial redundancies [22].

Other processes usefully convolutional neural networks. To keep away from computational redundancy, Long et al. [24] proposed a completely convolutional method to boom the efficiency through education on complete pix. It produces segmentation through pixel-smart prediction instead of unmarried opportunity distribution withinside the classification challenge for every photo. An instance of a modified model of such an method is U-Net [22]. Also, the usage of the switch gaining knowledge of method is some other method that has been broadly used these days in biomedical studies [28,29]. To cope with the restrict of information shortage in clinical imaging studies, this method employs a pre-skilled version from non-clinical pictures.

In breast imaging, the bulk of the present guides are that specialize in the usage of CNNs for mammography. Dhungel et al. [30] used deep gaining knowledge of for massive quantity segmentation; Mordang et al. [31] proposed using CNNs in microcalcification detection; and greater these days, Ahn et al. [32] proposed using CNNs in breast density estimation. In breast ultrasound imaging, Huynh et al. [28] proposed using a switch gaining knowledge of method for ultrasound breast photo classification. It became the simplest take a look at in breast ultrasonography, but it excludes most cancers detection.

A CNN has been proposed for denoising ultrasound pix, observed through some other CNN version for ultrasound photo category into benign and malignant cancerous pix on Mendeley Breast Ultrasound dataset [33] that has comprising of 250 pix. There are one hundred benign pix and one hundred fifty malignant pix [34]. Also, some other CNN has been advised to differentiate among malignant and benign breast lesions. This is a study that makes use of a deep gaining knowledge of method to obtain breast most cancers category in computerized breast ultrasound (ABUS) imaging. Additionally, used Multiview strategies, which allow conventional CNNs to analyze greater lesion capabilities from a couple of ABUS imaging photo perspectives simultaneously. Even so, the proposed CNN takes a uncooked photo as enter and learns the photo capabilities immediately, removing the want for a sequence of guide processing steps inclusive of breast lesion segmentation and function selection [35]. In this paper, we recommend using deep gaining knowledge of processes for computerized breast ultrasound most cancers category and segmentation. To display the benefits of deep gaining knowledge of processes, they examine the performances with the 3 distinctive size techniques and one new accumulated dataset [36].

## III. Methodology

### A. *Datasets and preprocessing*

This observe made use of a newly accumulated dataset of US photos in breast most cancers. The dataset became received from US structures with one of a kind specifications and at one of a kind times. The statistics offered withinside the article [36] evaluations the scientific photos of breast most cancers the use of an ultrasound scan. Breast Ultrasound Dataset pix are categorized into 3 types: ordinary, benign, and cancerous. The statistics accumulated consists of breast ultrasound photos amongst girls in Cairo, Egypt. in a while among 25 to seventy five years old. This statistics became accumulated in 2018. There are six hundred lady sufferers in all. The series consists of 780 pix, every of that's 500×500 pixels in size. The photos are in PNG format. The pix are divided into 3 categories: ordinary, benign, and malignant. There are 487 benign photos 210 malignant photos and 133 ordinary photos. In Fig.1 you could see 3 one of a kind photos from the noted 3 categories.

They produce an photo decision of 1280*1024. The transducer at the ML6-15-D Matrix linear probe variety from 1 to five MHz.

Ground truth (photo boundary) is done to make the ultrasound dataset usable. For every photo, a hand - drawn segmentation is created. Figure 2 indicates an instance of a masks picture. For every type of breast most cancers, 3 documents are generated. Each folder consists of pix from its respective magnificence. The photo call accommodates the magnificence call in addition to the photo quantity. In addition, the call of the masked photo has the call because the US photos with adding "_mask" to the quit call of the photo.

To use this dataset, we did a few preprocessing on photos. We placed unique photos and masks photos of 3 one of a kind categories, in folders as img and masks. Also, we offer a check dataset from the accumulated dataset. Although U-Net may be educated with a low quantity of photos we used preprocessing and statistics augmentation on photos to boom the quantity of statistics. During training, we use statistics augmentation via way of means of randomized scale of enter pix (from 0.five to 2.0) and randomized left-proper scaling flipping. And additionally, via way of means of randomly rotating the photos. We convert all photo sizes to 512 × 512. The pre-processed photo is changed to 512×512 patches to enhance fashions' overall performance and mitigate the excessive useful resource requirement.

For the training, the better-acting version at the validation set became selected for similarly evaluation. We have used statistics augmentation, wherein US photos had been horizontally flipped and blurred with Gaussian noise to beautify the training. Besides that, a preprocessing mechanism is proposed to cast off noise, objects, and muscle areas that could cause a excessive fee of fake positives. If any of the photos withinside the dataset have bizarre noise, the fashions couldn't discover the excellent capabilities and may have a excessive fake fine fee.

We used a noise discount system [37] to preprocess the uncooked photos into noise-unfastened photos for this observe. Furthermore, in breast most cancers detection, now no longer simplest need to the detection fee be excessive, however there may be additionally a want to discover the cancerous segment, with the intention to allow the surgeons and radiologists to quick take measurements and accurate it. Our fashions help them as it should be stumble on breast most cancers kind and segmenting the cancerous region.

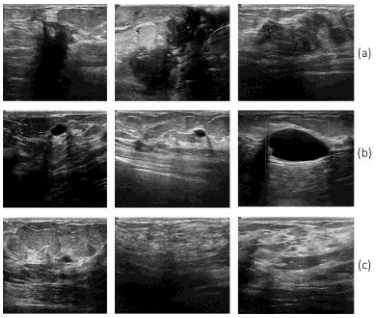


Fig. 1. Several US images presenting malignant cancer (a), benign cancer (b), and normal (c) used to develop the segmentation network

## B. Convolutional Neural Networks Architecture

Different CNN architectures have an effect on the overall performance of class and segmentation below a deep getting to know framework. We want to apprehend the impact of various CNN designs at the diagnostic gadget in our study. In this section, we furnished an outline of 5 one-of-a-kind CNN fashions which consist of VGG-16, ResNet-50, DenseNet-161, AlexNet, and U-Net. In addition, all CNN fashions have been educated from scratch on every photograph kind and used 80% and 20% of auto-shuffled records to the schooling and checking out procedure respectively (20% if schooling set allotted for validation set).

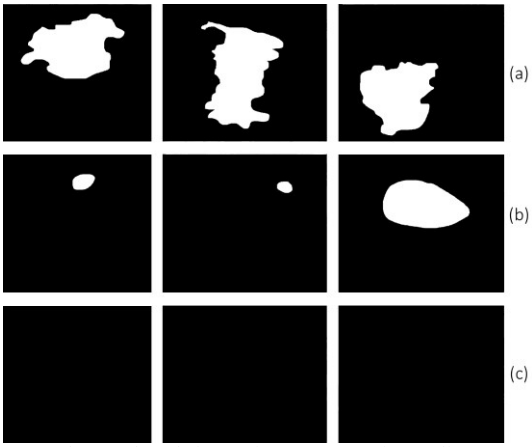


Fig. 2. Several ground-truth for US images presenting malignant cancer (a) benign cancer (b) and normal (c) breast used to develop the segmentation network

We enforce and take a look at the dataset on distinct gadget mastering and deep mastering-primarily based totally algorithms and approaches. Also, withinside the neural networks that we used and defined on this paper, we examined distinct parameters and the satisfactory outcomes are Have been positioned on this paper. For example, we attempted ResNet 18, ResNet-50, ResNet-101. Below, we listing a number of them which have the satisfactory overall performance withinside the class and segmentation project on average. The system of all proposed algorithms is proven in Fig.3. After making use of preprocess at the dataset, we feed CNNs with the unique photo and masks images (Fig.1 and Fig.2). Then, the stairs of function extraction segmentation and class were completed with distinct CNNs. Every time, the square field in Fig.3 is one of the following CNNs.

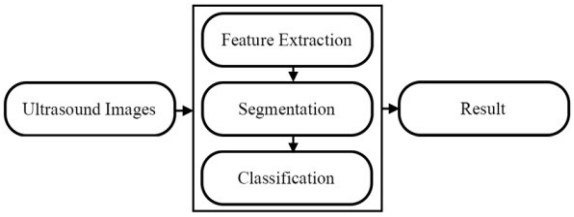


Fig. 3. Flowchart of implementation CNNs

### 1) ResNet-50

He et al. offered a residual Neural Network. [39] that imported a singular structure with a shortcut connection route that skips one or greater layers withinside the network. ResNet used the residual shape via way of means of including an

identification mapping to transform the unique characteristic to F(x) + x. The enter and output of residual block had been connected via way of means of a shortcut connection. Based at the advantages of the residual block method, in spite of 152 layers has decrease computational complexity than VGGNet. So, ResNet suggests proper overall performance in type and segmentation. We used ResNet with 50 layers in our study.

*2) DenseNet-161*

DenseNet is a densely linked convolutional neural community proposed through Huang [40], and the essential perception became that any tiers had an immediate relationship. Each layer's enter gets greater data from all preceding layers, and the function maps learnt through the layer also are despatched directly to all next layers as enter. The blessings of the DenseNet structure are decreasing the vanishing gradient problem, improving the transmission of the future, the usage of capabilities extra efficiently and decreasing the range of parameters to make the community quicker to be trained. We used the DenseNet version with 161 layers in our study.

*3) VGG-16*

The VGGNet version turned into proposed with the aid of using Simonyan [38], which seemed as an prolonged CNN structure of AlexNet. VGGNet version extracts extra records with the aid of using the use of extra hidden layers (19 layers on this task) due to the fact the smallest clear out out size (3 × 3) has a smaller receptive filed that enables to accumulate extra certain records from an image. However, VGG-sixteen is deeper than different common CNN structure it has extra hyper-parameters and extra at risk of the vanishing gradient problem. The structure of used VGG-Net is illustrated in Table.1.

Table 1. The VGGNet architecture proposed in our paper

| Filter Size | Layer Type | Number of filters |
|---|---|---|
| Input | | |
| 3 × 3 | Conv | 64 |
| 3 × 3 | Conv | 64 |
| 2 × 2 | Max Pooling | |
| 3 × 3 | Conv | 128 |
| 3 × 3 | Conv | 128 |
| 2 × 2 | Max Pooling | |
| 3 × 3 | Conv | 256 |
| 3 × 3 | Conv | 256 |
| 3 × 3 | Conv | 256 |
| 2 × 2 | Max Pooling | |
| 3 × 3 | Conv | 512 |
| 3 × 3 | Conv | 512 |
| 3 × 3 | Conv | 512 |
| 2 × 2 | Max Pooling | |
| 3 × 3 | Conv | 512 |
| 3 × 3 | Conv | 512 |
| 3 × 3 | Conv | 512 |
| 2 × 2 | Max Pooling | |
| FC | | |
| FC | | |
| FC-1 | | |
| Sigmoid | | |

*4) AlexNet*

AlexNet [41] is a highly sturdy version able to achieving excessive accuracies on extraordinarily tough datasets. Removing any of the convolutional layers, on the opposite hand, will extensively lessen AlexNet's performance. AlexNet is a main layout for any laptop imaginative and prescient paintings and can have wide-ranging makes use of withinside the synthetic intelligence laptop imaginative and prescient industry.

*5) U-Net*

U-Net is a custom designed and advanced model of a totally convolutional network [22] which can deal with the call for large-scale datasets in clinical and organic research. It is a CNN with skipping hyperlinks this is constructed on encoder-decoders. Ronneberger et al. [22] proposed U-Net to allow the usage of facts augmentation, such as the usage of non-inflexible deformations, that allows you to completely make use of the supplied annotated instance images for schooling the model. These traits suggest that the U-Net may doubtlessly supply ok consequences given the size of the on hand datasets now in use.

In phrases of layout and pixel-primarily based totally photo segmentation generated from convolutional neural community layers, U-Net beats different conventional models. Based on its structure it can have excessive accuracy even on datasets which have a small range of images. This layout changed into at first visible thru the observe of organic pictures. The measurement discount system withinside the top and width that we use throughout the convolutional neural community - withinside the 2d a part of the version, as it's far typically termed, the pooling layer is primarily based totally at the software of a length increase. By retaining the range of channels withinside the enter matrix static, the pooling layer minimizes top and width data. Each member of the image matrix is called a pixel, and the computation is a step used to decrease complexity. To summarize, the pooling layer is a pixel that suggests companies of pixels.

Such layers are designed to enhance the output's clarity. The sampled output is included with excessive-decision traits throughout the version for localisation. Based in this knowledge, a successive convolution layer tries to create a greater actual output. U-Net takes its call from the structure, which while visualized, seems just like the letter U. A segmented output map is generated from the enter pictures. The maximum remarkable characteristic of the layout withinside the 2d part. The convolution layers are the best ones which can be used. A ReLU activation characteristic turns on every everyday convolution process.

## C. Implementation and Training

We used Tensorflow and Keras frameworks primarily based totally on Python to put into effect all our 5 neural networks, education absolutely with our information and checking out on breast most cancers US images. We have evaluated the version the use of 10-fold go validation. We teach the version the use of stochastic gradient descent with a gaining knowledge of fee of 0.001, 60 epochs with a dropout fee of 33%. The wide variety of epochs changed into a hundred as in as which convergence has already took place while we achieved empirical experiment. To education our neural networks we used Google Colab Pro with 2GB RAM as much as 25GB, NVIDIA Tesla K80 as GPU and TPU. With those sources education every CNNs lasts 6 hours in average.

## IV. Results and Discussion

In this paper, we used breast most cancers ultrasound pictures to automate the class and segmentation of most cancers in pictures. So, our assignment is the aggregate of the class element and the segmentation element. In this section, we in comparison the diagnostic overall performance of all CNN architectures, together with VGG-16, ResNet-50, DenseNet-161, AlexNet, and U-Net. Furthermore, we listing the CNNs which accomplished the satisfactory overall performance at the take a look at set and compares overall performance amongst used one of a kind CNNs.

### *A. Classification*

In statistical analysis, 4 quantitative metrics have been used to assess the type part. Accuracy, precision, recall, and F1 score. (Table. 2) Also, Precision and Recall are not unusual place signs for comparing type performance [42]. Precision and Recall may be contradictory, so we used the F1 Score [43] for complete consideration.

$$\text{Accuracy} = (TP + TN) / (TP + FP + TN + FN) \quad (1)$$

$$\text{Precision} = TP / (TP + FP) \quad (2)$$

$$\text{Recall} = TP / (TP + FN) \quad (3)$$

$$\text{F1 Score} = (2 \times \text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (4)$$

Table 2. The average result of all CNN architectures. Accuracy, precision, recall, and F1 score in percentage for classification three different categories (malignant, benign, and normal). Bold indicates the best result.

| Method | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| VGG-16 | 84.57 | 89.34 | 73.64 | 80.73 |
| ResNet-50 | 84.57 | 88.1 | 75 | 81.02 |
| DenseNet-161 | 83.09 | 89.57 | 69.59 | 78.33 |
| AlexNet | 81.61 | 89.35 | **79.00** | **83.86** |
| U-Net | **87.86** | **91.04** | 64.18 | 75.29 |

### *B. Segmentation*

For the contrast segmentation part, we used VGG-16, ResNet-50, DenseNet-161, AlexNet and U-Net, CNN architectures. The fee characteristic and the metric for evaluating the overall performance of proposed techniques is intersection over union (IoU), Table three indicated the end result of all CNN architectures for segmentation via way of means of IoU metric.

$$\text{IoU} = (\text{mask} \cap \text{prediction}) / (\text{mask} \cup \text{prediction}) \quad (5)$$

Table 3. The result of all CNN architectures for segmentation three different categories (malignant, benign, and normal) and average result. Bold indicates the best result.

| Method | Category | IoU | Average |
|---|---|---|---|
| VGG-16 | Normal | 88.33 | 75.04 |
| | Benign | 75 | |
| | Malignant | 61.8 | |
| ResNet-50 | Normal | 91.18 | 76.42 |
| | Benign | 66.42 | |
| | Malignant | 71.65 | |
| DenseNet-161 | Normal | 79.1 | 78.19 |
| | Benign | 78 | |
| | Malignant | 77.48 | |
| AlexNet | Normal | 91.72 | 83.76 |
| | Benign | 84.23 | |
| | Malignant | 75.33 | |
| U-Net | Normal | 100 | 91.00 |
| | Benign | 79.27 | |
| | Malignant | 93.73 | |

Examples of instances and the overall performance of the tumor segmentation the usage of U-Net from the dataset is illustrated in Fig.4. The white suggests the floor reality or anticipated elements which might be segmented automatically. The first row suggests a tough case wherein the most cancers is malignant. The 2d row illustrates a case wherein the most cancers are positioned near the pinnacle and U-Net detected the tumor form very near the floor reality. The 0.33 row suggests a photograph with the perfect shadow and the proposed deep studying techniques detected that there isn't always any tumor in this photograph.

The snap shots with extra photograph info assist the deeper community structure offer higher output, in keeping with the consequences at the dataset. Other CNNs additionally outperforms VGG in phrases of efficiency. There might be reasons: (1) deeper traditional CNN structure won't be capable of put off extra complicated and precise capabilities from a small photograph due to their depth. (2) On small information sets, the usage of a deeper CNN with extra parameters can motive overfitting issues. Since the relationship method should enhance the deep CNN structure to analyze extra capabilities efficiently, that ResNet and DenseNet used it to attain message rectification, stopping inter-layer transmission loss and resolving the gradient disappearing problem.

## V. Conclusion

In our have a look at, we endorse a CAD device for tumor prognosis the use of a totally convolutional neural network, U-Net to categories and localize breast most cancers. For this task, we used unique tumor images, segmented tumor images, and tumor mask withinside the US images. Our have a look at established the CAD device primarily based totally on CNN structure combining a couple of tumor capabilities that would offer a very good end result to diagnose a tumor in a affected person with breast most cancers. For classification, we used the accuracy metric and for the segmentation task, we used the IoU metric. Also, we as compared our outcomes with four special neural networks (VGG-16, ResNet-50, DenseNet-161, and AlexNet).

In consequence, destiny paintings will cognizance on growing the accuracy through including greater education records in preference to records augmentation and pass validation, the use of and manipulating neural networks to create greater custom designed and task-primarily based totally CNN extending our works to breast ultrasound most cancers segmentation and classification, and compare the overall performance of the entire CAD framework.

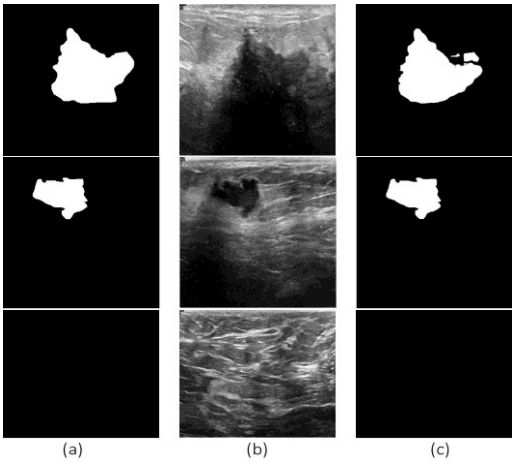


Fig. 4. Representative segmentation results using U-Net (a) mask image, (b) original image, and (c) predicted image

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