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# Applying Deep Learning Models to Breast Ultrasound Images for Automating Breast Cancer Diagnosis

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***Abstract*— Breast cancer is a result of uncontrolled human cell division. The vast growth of breast cancer patients has been an issue worldwide. Most of the patients are women, but breast cancer also affects men with a much lesser percentage. Breast cancer might lead to death for those who are suffering from it. Numerous types of research have been done to make an early diagnosis of breast cancer. It has been proven that the tumor can be detected by using an ultrasound image. Artificial Intelligence techniques have been used to detect breast cancer fundamentally. This paper studies the effectiveness of deep learning (DL) techniques in automating breast cancer diagnosis. Subsequently, the paper evaluates the diagnosis performance of three DL models utilizing the criteria of accuracy, recall, precision, and f1-score. The Densenet-169, U-Net, and ConvNet DL models are selected based on the examination of the related work. The DL diagnosis process involves identifying two types of breast cancer tumors: benign and malignant. The evaluation outcomes of the DL models show that the most effective model for diagnosing breast cancer among the three is the ConvNet, which achieves an accuracy of 91%, a recall of 83%, a precision of 85%, and an F1-score of 83%.**

***Keywords*— Breast cancer; malignant, benign; ultrasound images; convolutional neural network; Densenet-169; ConvNet; U-Net.**

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## I. Introduction

The rapid growth in cancer patients has been a critical issue [1]. Cancer results from uncontrolled mitosis in human cell division, forming a tumor [2]. According to [3], 11.3% (1.7 million) of patients were affected by breast cancer in 2015. This amount is estimated to grow more over the next 20 years. According to research statistics, 8% of women worldwide could be diagnosed with breast [4]. Numerous cancer patients died due to breast cancer. Death happens because most breast cancer patients have no symptoms, and the cancer is detected at an advanced stage. Numerous types of research have been done to help cancer patients survive this deadly disease. Breast cancer begins in the cells, which are the milk-producing glands. Generally, two types of tumor cells are diagnosed: malignant and benign. A malignant tumor is known as a cancerous tumor in the human body. A benign tumor grows slowly, does not spread in local structure, and usually is not considered harmful. Breast cancer has shown the highest rate of cancer death. It is reported that about 25% of deaths are caused by breast cancer in Malaysia, and the percentage of Malaysian women who are at risk of cancer is about 5%. In the United States and Europe, the possibility of women having breast cancer is about 12.5% [5]. These numbers are expected to be increasing over time. It is important to detect breast cancer tumors at early stages to increase the survival rate of the patients. Thus, women have to attend regular checking for early breast cancer detection [6]–[8]. The regular breast cancer check-up doesn't confirm a hundred percent cancer-free results due to the problematic identification of the symptoms. Therefore, precise and fast breast cancer detection is crucial for potential cancer patients.

Pathologists and doctors detected this cancer by observing ultrasound images. However, this manual process will undoubtedly take specialists' time and might effort and affect the patient's health condition. Thus, a computer-aided diagnosis (CAD) helps diagnose potential cancer patients in their early stages and provides appropriate treatment [9]–[11].

Machine learning (ML) and deep learning (DL) techniques have been widely applied in various medical areas over the past few years and have proved to be powerful tools for solving complex problems. DL techniques such as convolutional neural networks (CNN) have been intensively utilized for automating the diagnosis of diseases in the medical field, including cancer detection [10]–[13]. As technology grows, machines and algorithms have automated cancer detection techniques to manifest feasible solutions. Recently, with the help of technology, there have been a few methods or approaches to detecting breast cancers, including X-ray mammography, ultrasound images, computed tomography, magnetic resonance imaging (MRI), and histopathology images [4]–[7]. DL may allow us to eradicate all forms of cancer in the future altogether. Such new technology can assist us in identifying cancer in its early stages, which helps in cancer treatment [14], [15].

MRI is one of the best imaging approaches that help detect breast cancer. This method allows the detection of the tumor and the tumor progression. MRI images have been proven to have impacted the medical imaging analysis field due to their ability to provide the information that medical experts require. The research work by Mohsen et al. [16] deploys k-nearest neighbor (KNN) and deep neural network (DNN) for diagnosing brain tumors from MRI images. The test results show that the classification accuracy rate for the KNN is the lowest, and the DNN scores the highest accuracy at 97%.

Researchers have highlighted the limitations of the most commonly used breast cancer detection methods based on digital mammography [4]. Breast cancer detection using mammography is not equally effective for all women. The average accuracy result of mammography for breast cancer detection is 85%. Subsequently, researchers have recommended ultrasound imaging as a better approach to cancer detection due to its versatility, sensitivity, and safety. However, under certain circumstances, ultrasound images depend more on the radiologist's diagnostic ability [1]. This approach has implementation challenges, especially in third-world and developing countries, due to a need for more experts in the field. Subsequently, researchers decided to create a testing platform for automating cancer detection based on ultrasound imaging with the help of CAD. The introduction of DL helps in this ultrasound imaging cancer detection [14], [15]. Accordingly, this helps raise the sensitivity to cancer detection by 10%.

Nallamala et al. [5] state that software solutions play a dynamic role in judging imprecise and uncertain knowledge of cancer cells in a human's body. They propose an expert system based on ML algorithms for breast cancer forecasts to provide additional support in examining breast cancer. They use digital mammography and the Wisconsin breast cancer dataset screening for the diagnostic process. They used three machine learning models: support vector machine (SVM), KNN, and logistic regression (LR). The results obtained by that research clearly show that KNN has performed the best as it acquired an accuracy of 89% compared to SVM and LR. They both achieved relatively the same accuracy, which amounted to 87%.

Breast ultrasound image segmentation and classification are critical steps in breast cancer detection. Yap et al. [8] collected a breast ultrasound images (BUI) dataset from the US healthcare systems. The dataset was then split into two sections, A and B. The A dataset consists of 306 pictures that are 60% malignant, whereas the B dataset consists of 163 images that are 53% malignant. They developed a CAD that helps radiologists and pathologists diagnose the ultrasound images present in the ultrasound images. In this research, three types of DL algorithms have been used for breast image classification. A patch-based approach using transfer learning, U-net, and LeNet, with fully convolutional networks, has been tested with two datasets, A and B. The metrics used in this research are false-positive, true-positive, and f-measures. The investigation results show that the patch-based approach using LeNet is more accurate for breast cancer detection of dataset B, and the FCN-AlexNet combined with transfer learning is more accurate for dataset A. The DL techniques comply with the specific characteristics of the provided datasets [8].

This paper evaluates the performance of DL models in developing CAD for automating breast cancer detection. Three types of CNN models, U-Net, ConvNet, and DenseNet-169, were selected to obtain accurate and precise breast cancer image segmentation and classification. The rest of the paper is organized into three sections of materials and methods used, including the description of the DL model and the BUI dataset, a discussion about the obtained results, and finally, conclusions that are made based on the tested DL models on the dataset of breast ultrasound images.

## II. Material and Method

The CRISP-DM model is a step-by-step approach to data mining activities. It is appropriate for applying DL in the diagnosis of breast cancer. Developed with European Community funding, CRISP-DM comprises six phases. The project development life cycle can be divided into six stages: understanding of the project business background, data understanding and preparation, and solution modeling, evaluation, and deployment [18]. These phases are intended to establish a proper DL model development framework. Fig. 1 shows the processes of the CRISP-DM methodology.

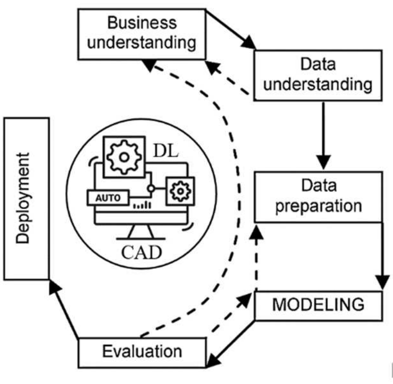


Fig. 1 CRISP-DM process methodology [18]

The methodology starts with the business domain, where project goals and needs are set from the clinical point of view, such as decreasing diagnostic errors and increasing early diagnosis rates. This phase ensures that all the activities carried out in the project meet the primary goal of creating a CAD system that improves radiologists' decision-making support.

During the data acquisition and cleaning steps, the breast cancer dataset is obtained and analyzed to identify the data's nature and solve the possible data quality problems. The data preprocessing techniques applied include normalization, resizing, and augmentation to make sure that the dataset used to train the DL models is optimal. The classification of benign and malignant categories must be precisely located in the dataset. The dataset is then further divided into training and test sets for testing purposes. This phase leads to the modeling phase, where the DL architectures are designed and optimized.

The modeling step includes choosing suitable DL architectures, in which Densenet-169, U-Net, and ConvNet DL are selected. These models are fine-tuned and assessed based on performance measures such as accuracy, recall, precision, and F1-score, with the help of confusion matrices for tuning. During the deployment phase, these models are incorporated into a CAD system for practical use, whereby the system diagnoses the radiologist. This structural pattern allows for the improvement of diagnostic accuracy and efficiency in detecting breast cancer, and the developed system is reliable and adaptable.

### *A. Dataset*

Breast cancer can be characterized by the expression of progesterone or estrogen receptors and the presence of the ERE2 gene's amplification. There are two types of tumor cells being diagnosed: malignant and benign. This project uses the breast ultrasound images (BUI) dataset. This dataset contains 913 image samples for benign and malignant. The BUI dataset has been obtained from the Kaggle.com data repository [19]. The most important thing about the dataset is that it has been widely used for various testing of breast cancer detection or diagnosis. Fig. 2 shows some samples of malignant and benign images obtained from the breast ultrasound images dataset.

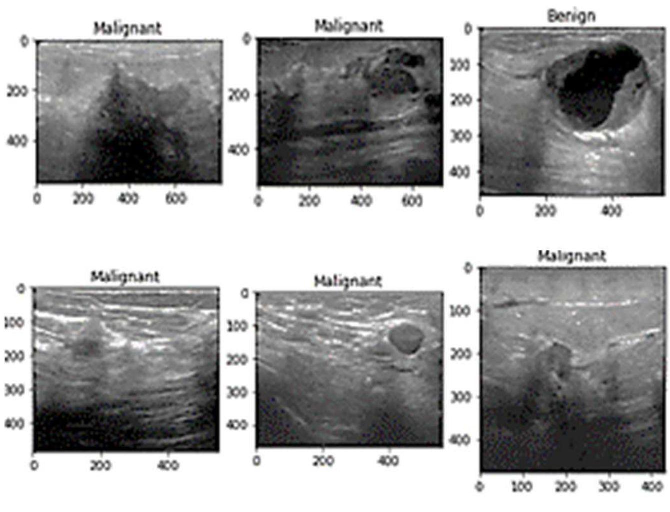


Fig. 2 Sample of images in the BUI dataset [19]

### *B. Convolutional Neural Network*

The most dominant architecture in DL of image processing is Convolutional Neural Network or, in short, CNN. CNN has become a vital image analysis tool and is well known for enhancing the accuracy of images. CNN works within multi-layer classes using a single neural network and a well-trained end-to-end image processor that helps raw images have a classified output. CNN works specifically in image processing analysis, and it is one of the computational models composed of multiple layers to extract the features of raw data. CNN trains from datasets that contain a large number of images to learn more about these images. The CNN consists of a few layers: starting with the input layer, convolution layer, pooling layer, fully-connected layer, and ending with the output layer, as shown in Fig. 3. These layers represent a hierarchical abstraction of the CNN design.

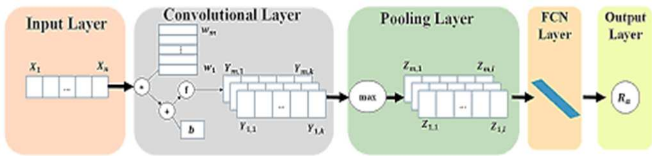


Fig. 3 CNN Layers [20]

DL in the CNN consists of many types suitable for prediction, classification, and visualization. It is understood that the data provided for breast cancer screening may be unstructured [9]. CNN works with structured, unstructured, and semi-structured data [21]. It works specifically in image processing analysis, and it is one of the computational models composed of multiple layers as follows:

*1) Convolution Layer:* The convolution layer usually consists of a learnable set of filters. Each convolutional layer is associated with a parameter. The convolution layer works in a 3D structure, and its neuron computes the weights and volume in the layer [15].

*2) Pooling layer:* The pooling layer reduces the size of convolved features. This issue results in a reduction in the required computational power. It provides an activation map and applies a non-linear down-sampling on the activation maps. Throughout the process, this layer can perform two types of operations: max pooling and average pooling. This process can also be called a sub-sampling process.

*3) Fully connected layer:* This layer functions as a brain to learn about an image's features at a pixel level. The fully connected layers can be viewed as the final learning phase. Multi-view CNN adapts sketches, 2D images, and 3D images. Multi-view CNN architecture learned to identify 3D shapes in an image by comparing different shapes views through a view-pooling layer. Multi-view CNN helps to get accurate information compared to a single view [7].

Several DL models are introduced based on the CNN architecture, including U-Net, ConvNet, and DenseNet-169.

*1) U-Net:* The U-Net has a CNN architecture mainly used for biomedical image segmentation. It is based on a symmetric architecture with an encoder-decoder structure; the encoder (contracting path) applies two 3×3 convolutions followed by a Rectified Linear Unit (ReLU) and a 2×2 max-pooling for down-sampling. The decoder (expanding path) employs the up-sampling technique combined with a 2*2 convolution, also known as up-convolution, and then a feature map from the corresponding encoder path, which helps localization [8]. This architecture allows the network to learn high-level features and low-level contextual information, which is useful when working with image pixel-level segmentation.

*2) ConvNet:* A ConvNet is a type of CNN widely used in visual data analysis. The architecture is a stack of layers capable of automatically and adaptively learning spatial hierarchies of features from the input images. The essential parts are the convolutional layers that use some filters to perform feature extraction. These pooling layers help to decrease spatial dimensions to address the issues of computational complexity and overfitting and fully connected layers that integrate the previous features to perform classification or regression tasks [13]. These layers can learn features from the images through receptive fields that are used to capture spatial relationships between the pixels. This means that convolutional layers can identify edges, textures, and even more complex features of the images, making them very suitable for image recognition, classification, and detection tasks.

*3) DenseNet-169*: DenseNet-169 is a type of CNN architecture with a dense connectivity pattern where every layer is connected to the other layer in a feed-forward manner. This architecture has 169 layers, including convolutional, pooling, and fully connected layers. The main idea of DenseNet-169 is to create dense blocks in which every layer takes input from all previous layers and feeds its output to all subsequent layers [17]. This technique increases the feature reuse and the flow of gradients. This high connectivity also reduces the number of parameters and avoids the gradient vanishing problem, enabling the development of deeper architectures that are both computationally efficient and accurate. DenseNet-169 is highly effective for complicated image classification and segmentation applications due to its high performance with fewer parameters than CNN.

### *C. Evaluation Metrics*

This work compares the classification accuracy of the U-Net, ConvNet, and DenseNet-169 models. The evaluation metrics used in the experiments are accuracy, recall, precision, and F1 score, represented as a confusion matrix and defined as follows [22], [23].

*1) Accuracy:* The accuracy represents the proportion of total correct predictions. It is calculated using the counts of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). The formula for accuracy is given below:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (1)$$

*2) Recall: S*ensitivity or recall shows the proportion of positive cases that were correctly identified.

$$Recall = \frac{TP+TN}{TP+FN} \qquad (2)$$

*3) Precision:* Precision calculates the proportion of the predicted positive cases, as defined in the formula.

$$Precision = \frac{TP}{TP+FP} \qquad (3)$$

*4) F1-Score:* The F1-score, or F1-measure, considers both precision and recall to offer a balanced measure of the classifier's performance. The F1-score is a more reliable indicator of a classifier's performance than standard accuracy in imbalanced datasets. It is calculated using the following formula:

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision+Recall} \qquad (4)$$

## III. Results and Discussion

DL has been widely adopted in research and development of CAD projects. Many medical diagnosing problems entail image processing and classification solutions. The sudden demand for medical image classification is due to the availability of CAD data in modern clinics. Image classification often employs a DL CNN-based models for CAD data classification, including breast images. These models can be categorized into the de novo trained and transfer learning-based models.

This work aims to test and identify the best classification model for breast cancer diagnosis. It applies three DL models to classify breast cancer images from the BUI dataset. The three DL models are U-Net, ConvNet, and DenseNet-169 [8], [24]. All three models are tests based on dividing the dataset by a 70:30 ratio of training and testing. The epoch for training is 100. Fig. 4 shows the graph of loss and accuracy for the three models during the training phase.

a. U-Net model

b. ConvNet model

c. DenseNet-169 model

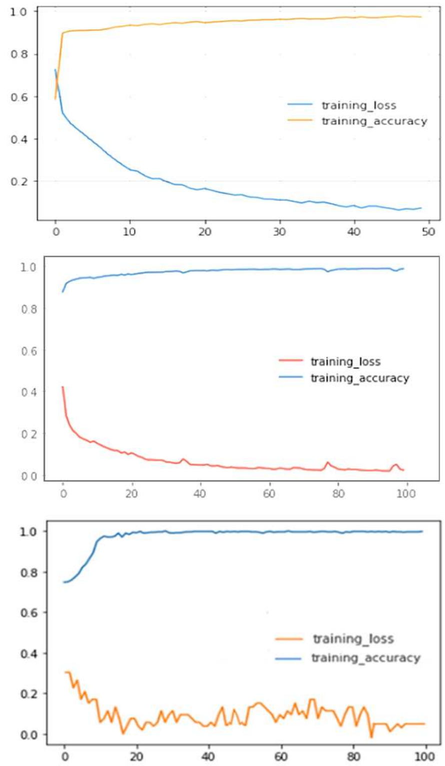


Fig. 4 Training loss and accuracy result of the models

TABLE II
EXPERIMENT RESULT

| Model | Split ratio | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|---|
| U-Net | 70:30 | 0.82 | 0.77 | 0.77 | 0.77 |
| ConvNet | 70:30 | 0.91 | 0.85 | 0.83 | 0.83 |
| DenseNet-169 | 70:30 | 0.73 | 0.72 | 0.70 | 0.70 |

The three figures show that the most stable model during the training is the ConvNet, followed by the U-Net and the DenseNet-169. The classification performance of three DL models in the testing phase is evaluated and compared in terms of accuracy, recall, and precision, and f1-score metrics.

The results of the evaluation metrics for the tested U-Net, ConvNet, and Densenet-169 models are shown in Table II.

From Table II of the results and the statistical analysis, we can see that the ConvNet model has outperformed all other models by a considerable margin, reaching an accuracy of 91 % and a precision of up to 85%. The accuracy score of the U-Net model is 0.82%, and the accuracy of the DenseNet-169 model is 73.0%. The DL is adaptable to the specific characteristics of the breast ultrasound image datasets provided. Hence, comparing the three types of DL shows different results for the tested dataset.

## IV. Conclusion

Cancer is one of the most deadly diseases that have targeted human beings. It is usually diagnosed at a very advanced stage when it is not easily curable. Breast cancer is complicated to detect at an early stage and is the third deadliest form of cancer, with prostate and pancreatic cancer being the first and second, respectively. This is a clear indication of the need to develop better breast cancer diagnostic techniques to aid in early identification and treatment. This paper analyzes and compares three selected DL types of CNN to classify breast cancer images. The performance of the U-Net, ConvNet, and DenseNet-169 models is tested on the breast ultrasound images. The test results are compared based on the accuracy, recall, precision, and F1-score evaluation metrics. The results indicate that the ConvNet model has the highest accuracy score of 91%, the highest precision of 85%, the highest recall of 83%, and the highest F1 score of 83%. The results of the three DL models in this work suggest improving the ConvNet model for enhancing the automated breast cancer diagnosis by incorporating transfer learning with pre-trained networks like ResNet or DenseNet. Also, in the data preparation phase, extensive data augmentation is used to enhance the generalization of the trained data.

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