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Research article

# An approach for classification of breast cancer using lightweight deep convolution neural network

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ABSTRACT

The rapid advancement of deep learning has generated considerable enthusiasm regarding its utilization in addressing medical imaging issues. Machine learning (ML) methods can help radiologists to diagnose breast cancer (BCs) barring invasive measures. Informative hand-crafted features are essential prerequisites for traditional machine learning classifiers to achieve accurate results, which are time-consuming to extract. In this paper, our deep learning algorithm is created to precisely identify breast cancers on screening mammograms, employing a training method that effectively utilizes training datasets with either full clinical annotation or solely the cancer status of the entire image. The proposed approach utilizes Lightweight Convolutional Neural Network (LWCNN) that allows automatic extraction features in an end-to-end manner. We have tested LWCNN model in two experiments. In the first experiment, the model was tested with two cases' original and enhancement datasets 1. It achieved 95 %, 93 %, 99 % and 98 % for training and testing accuracy respectively. In the second experiment, the model has been tested with two cases' original and enhancement datasets 2. It achieved 95 %, 91 %, 99 % and 92 % for training and testing accuracy respectively. Our proposed method, which uses various convolutional network to classify screening mammograms achieved exceptional performance when compared to other methods. The findings from these experiments clearly indicate that automatic deep learning techniques can be trained effectively to attain remarkable accuracy across a wide range of mammography datasets. This holds significant promise for improving clinical tools and reducing both false positive and false negative outcomes in screening mammography.

## 1. Introduction

Breast cancer diagnosis involves different methods such as mammography, ultrasound, MRI, and biopsy. Mammography, a low-dose X-ray, is standard for screening women over 50. Ultrasound uses sound waves to investigate abnormalities found during mammography. Biopsy, the definitive method, involves analyzing a small sample of breast tissue. Further testing determines the

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cancer stage and treatment plan. Early detection through regular screening improves treatment success. MRI, a non-invasive technique using magnetic fields and radio waves, provides detailed images, commonly used for high-risk patients or clarifying abnormalities found during other screenings [1]. Cancer encompasses a broad spectrum of diseases that can impact various regions of the body. It is characterized by the uncontrolled growth and division of abnormal cells, leading to the formation of tumors that can spread to nearby body parts and other organs. Breast, rectum, colon, prostate, and lung cancers are among the most prevalent types, causing almost 10 million deaths globally in 2020, representing about one-sixth of all deaths. Breast cancer, affecting millions of women worldwide, is a serious disease, but early detection through screening mammography can lead to effective treatment and cure. Screening mammography, an X-ray technique, helps identify breast cancer in its early stages, allowing prompt intervention. Women should be vigilant about any breast changes and consult their healthcare provider for regular screenings and early detection, which can significantly improve outcomes [2].

Breast cancer stands as the second most common cause of mortality among women globally. It frequently emerges without noticeable warning signs or symptoms, underscoring the importance of early detection and regular screenings. Despite progress, disparities in breast cancer outcomes persist due to factors such as socioeconomic status, race/ethnicity, and geographic location. Women residing in low- and middle-income countries encounter significant barriers in accessing both screening and treatment services, resulting in delayed diagnoses at later stages of cancer progression. Consequently, these women experience poorer outcomes in terms of survival rates and overall prognosis. Women of color in high-income countries also experience higher mortality rates, highlighting the need for targeted interventions and awareness. Prevention and early diagnosis remain crucial, with regular mammography screening playing a vital role in detecting breast cancer early. Maintaining a healthy lifestyle and being aware of family history and genetic risk factors can also reduce risk. Research advancements continue to improve outcomes, but efforts to increase access to screening and treatment, especially in underserved communities, are essential in reducing the global burden of this disease [3].

Breast neoplasms can be categorized into three basic forms: benign, in-situ carcinoma, and invasive carcinoma. The benign tumour causes only slight structural changes in the breast and is not considered a malignancy. It poses no immediate threat and is not dangerous. While in-situ cancer does not spread to other organs, it solely affects the mammary duct lobule system. If found early, this kind of cancer can be properly treated. The cells of the lobules, which oversee milk production and duct draining to the nipple, are where invasive cancer generally develops. These cancer cells gradually infect the neighboring healthy tissues and lymph nodes under the arms, opening a doorway for the disease to spread to other bodily organs [4].

Early and accurate breast cancer diagnosis is vital for enhancing survival rates. Various imaging techniques are being developed to achieve timely detection and aid in screening, diagnosis, and providing confidence to medical professionals. Modern imaging techniques like histopathology, MRI, CT, PET, thermography, mammography, and ultrasound are used to diagnose breast cancer. Mammography, introduced in the late 1970s, is considered a gold standard for early breast cancer diagnosis. It uses x-ray images to screen the breast area and detect differences in density, reflecting various tissue types. Mammography is particularly sensitive to microcalcifications and calcification clusters, making it valuable in diagnosing Ductal Carcinoma in Situ (DCIS) [5–7].

Ultrasound imaging devices can significantly improve tumor detection rates, reducing unnecessary biopsies and leading to cost savings. Additionally, ultrasound is a safer option as it does not use ionizing radiation, making it more affordable and portable than mammography machines. However, ultrasound is typically used in combination with mammography and histological methods for confirming breast cancer results [8]. On the other hand, Magnetic Resonance Imaging (MRI) is highly sensitive and efficiently displays breast lesions' size, shape, and location through multi-planar scanning and 3D reconstruction. CT images have also been utilized for preoperative staging in breast cancer patients, especially those with pulmonary symptoms, and have proven useful in predicting lymph node metastasis [9].

An alternative imaging technique for BC diagnosis is breast thermography, which employs an infrared camera to detect heat emissions from the intended body area. Due to the increased amount of heat produced by malignant cells, heat patterns are important signs of breast abnormalities. In contrast to other breast cancer imaging techniques, breast thermography is painless, non-invasive, non-contact, and safe for the patient, therefore it may be utilized for yearly physicals [10].

## 2. Related work

A review of CAD systems for breast cancer detection was carried out, comparing various methods and procedures at various crucial stages. Image pre-processing, which initially purifies and improves the quality of medical images is followed by image segmentation, which can be accomplished using either a discontinuity-based, similarity-based, or other approach. To extract features, one of three methods is used: shape-based descriptors, textural descriptors, or color-based descriptors. Both supervised and unsupervised algorithms for classification are known [11–15].

Machine learning is a branch of artificial intelligence that empowers computers to learn and enhance their performance through experience, without requiring explicit programming instructions. In the context of breast cancer detection, machine learning algorithms are trained on large datasets of medical images, such as mammograms, to identify patterns that are associated with breast cancer. One key advantage of ML is its ability to identify subtle features in medical images that may not be visible to the human eye. By analyzing many images, machine learning algorithms can detect even the smallest abnormalities and patterns that may show the presence of cancer. There are a variety of ML algorithms that have been developed for breast cancer detection, including CNNs, SVMs, and decision trees. These algorithms are trained using large datasets of medical images, often consisting of thousands or even millions of images. Once trained, they can be used to analyze new images and provide a diagnosis or identify areas that require further investigation. Overall, machine learning has the potential to be a powerful tool in the fight against breast cancer. By improving our

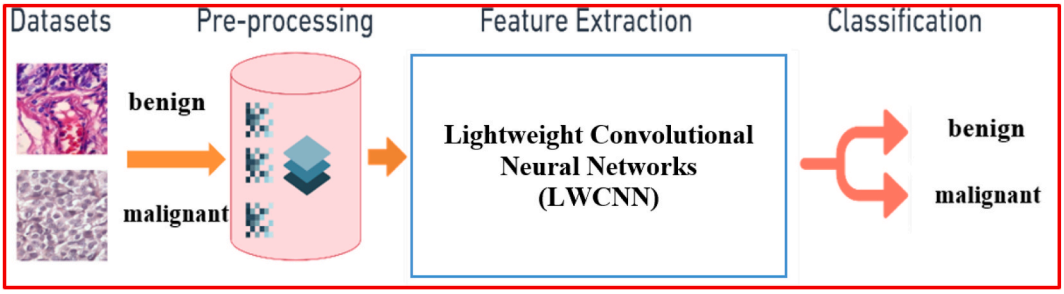


**Fig. 1.** Overview of the methodology.

ability to detect cancer early, we can increase the chances of successful treatment and improve outcomes for patients. Machin learning and image processing techniques in medical image analysis is a rapidly growing field that is transforming the way we diagnose and treat diseases. By leveraging sophisticated neural networks, deep learning algorithms can quickly and accurately analyze vast amounts of medical image data, detecting even the most subtle abnormalities that might otherwise go unnoticed. This technology has enormous potential to revolutionize healthcare by enabling earlier diagnoses, personalized treatments, and better patient outcomes. From detecting cancerous cells in mammograms to identifying neurological disorders in brain scans, ML are vast and varied [16–24].

Over the past few years, numerous researchers have explored the classification of malignant and non-malignant breast cancer using a variety of neural network classifiers. These efforts have yielded promising results, highlighting the potential of machine learning techniques for improving the accuracy and efficiency of cancer diagnoses. The researchers Ragab DA et al. have developed a new computer-aided design model that can accurately classify tumors as either benign or malignant based on mammogram images. This method utilizes a segmentation approach in two distinct ways: first, to physically identify the region of interest (ROI), and second, to employ threshold and region-based strategies. By utilizing these two segmentation approaches, the researchers aim to enhance the precision and accuracy of their results. To enhance accuracy, the researchers utilized DCNN for feature extraction. In addition, they replaced the final fully connected layer with SVM, which helped to further improve the model's accuracy. This approach demonstrates the potential of combining different types of machine learning techniques to achieve better results. The DDSM dataset was subjected to a segmentation procedure, which yielded interesting results. Specifically, the accuracy achieved using the first segmentation technique was higher than the accuracy achieved using the subsequent technique. These findings suggest that the initial segmentation approach may be more effective in this dataset [25]. In their recent study, Hua Li et al. [26] introduced a new neural network model called Dense Net-II, which represents an improved version of the existing DenseNet model. Specifically, the researchers replaced the first 3x3 convolution layer with an inception layer, resulting in a more efficient and effective model for classification tasks. These findings highlight the potential of continually refining and updating machine learning models to achieve better results. The researchers' approach effectively addresses the issue of overfitting, which can be problematic in deep and wide networks with numerous parameter configurations. To mitigate this issue, the mammogram images are pre-processed before undergoing data enhancement techniques, which help to prevent overfitting due to insufficient data. These findings highlight the importance of careful preprocessing and data enhancement in machine learning applications. The initial convolution layers in DenseNet were substituted with Inception Net, and the results were validated using a 10-fold cross-validation approach. In Ref. [27] various approaches of classification for distinguishing between malignant and benign lesions. Authors in Ref. [28] propose a deep learning (DL) approach utilizing a convolutional neural network (CNN) with a MobileNet architecture to extract relevant pictorial information for breast cancer classification. Their lightweight DL model demonstrates high accuracy while utilizing fewer computational resources, making it suitable for early-stage breast cancer detection. The proposed model's effectiveness is further enhanced by employing categorical cross-entropy as the loss function and incorporating a chi-square test during the classification stage. The authors trained their model on Google Colab for 280 epochs, leveraging a powerful GPU configuration. Their results indicate a significant improvement of over 11 % in the accuracy of histopathological image classification of breast cancer when compared to other state-of-the-art methods.

## 3. Dataset and methodology

In this paper, four stages are adopted as a methodology: obtaining the dataset, preprocessing data, feature extraction, and classification. The steps of the adopted methodology are presented in detail in Fig. 1. The CNN-based breast cancer image classifier framework was executed using MATLAB 2021a on a Windows 10 operating system with 16 GB RAM. The training process utilized an AMD Ryzen 5 3550H CPU and Radeon Vega Mobile GFX 2.10 GHz. The maximum number of iterations was set to 1240, and the batch size was set to 32. The model was trained for a total of 10 epochs, with each epoch consisting of 124 iterations covering the entire training dataset (see Fig. 2).

### *3.1. Dataset*

The Breast Cancer (BC) scan images downloaded from two types of datasets from Kaggle [29,30].

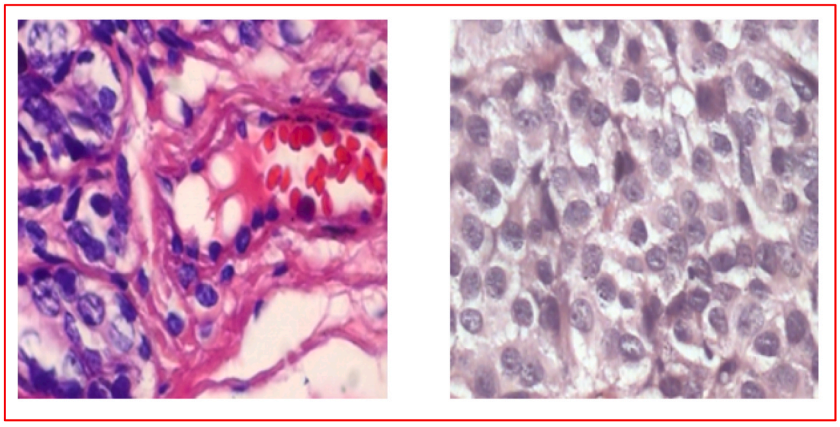


**Fig. 2.** Samples of the BC images used in this study (dataset 1) [29].

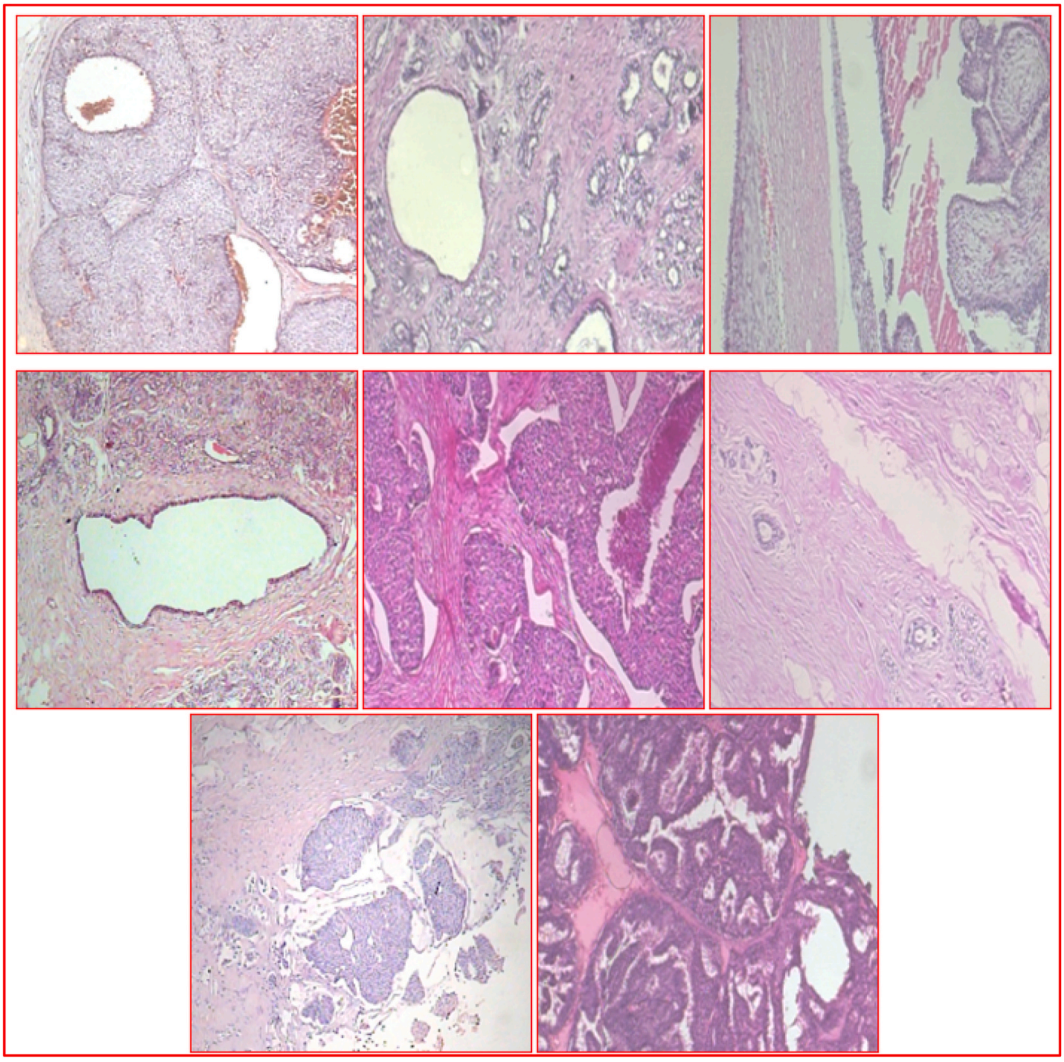

**Fig. 3.** Samples of the BC images used in this study (dataset 2) [30].

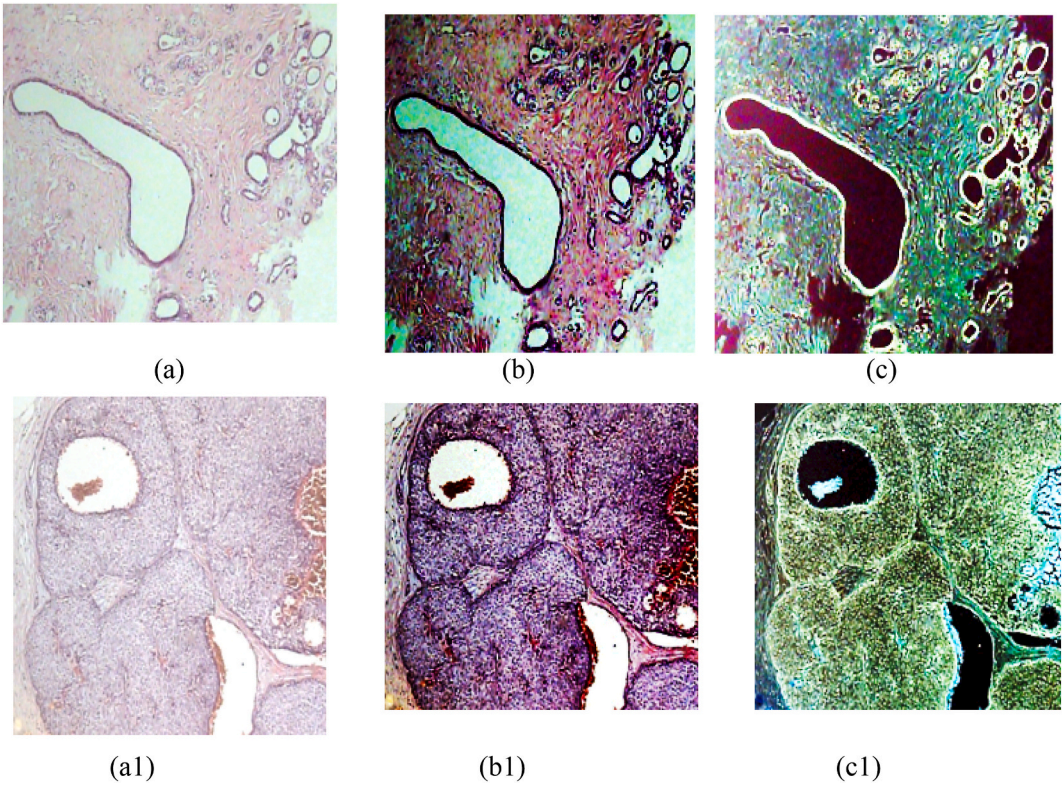


**Fig. 4.** Samples of the breast cancer images to (dataset 1) in (a1) and enhanced image with histogram equalization in (b1) enhanced image with Complement in (c1).

- In the first dataset, Sourabh Kumar [29] collected 2480 BC images. He posted the dataset under the title (unnormalized breast cancer histopathology) in November 2022. The dataset is organized into two folders (benign and malignant) and contains 1240 BC images for each image category. Fig. 1 illustrates samples of BC images used in this research.
- The second dataset [30] "Breast Cancer Hi "stopathological" Image Classification" (BreakHis) consists of 9109 microscopic pictures of breast tumor tissue obtained from 82 individuals utilizing different magnification settings. It now has 2480 benign and 5429 malignant samples, as shown in Fig. 3.

### *3.2. Pre-processing of image data*

In this research work, we utilized two methods for data pre-processing which are histogram equalization and complement. Based on our previous research, utilizing techniques to improve low medical images quality can significates enhance the accuracy rate of Classification [31]. The output of applied these methods on the datasets used on our experimental as shown in Fig. 4 for the 2-class of dataset-1, and Fig. 5 for 8-class of dataset-2.

### *3.3. The proposed model*

The proposed architecture consists of two main parts; the first part is the data augmentation using original data augmentation techniques such as (Reflection, Translation, and Scale). In the second part, we designed a new model called Lightweight Deep Convolution Neural Network (LWDCNN) model. In part one, CNNs are a data-hungry method, and the greater the number of data, the greater the accuracy and the lower the loss. Therefore, we proposed increasing the dataset using some types of data augmentation, such as (Reflection, Translation, and scale) in both dimensions X and Y. In part two, a new CNN model is proposed called LWCNN to improve performance in the feature extraction and classification with low numbers of parameters. Fig. 6 illustrates the architecture of the LWCNN, comprising of five convolutional blocks. Each block consists of a batch normalization layer, a Leaky ReLU layer, and a max-pooling layer. For further specifics regarding the LWCNN, please refer to Table 1.

## 4. Experimental results

In this section, we present the experimental results of our low-complexity and compact CNN model, referred to as LWCNN. This paper used two types of data sets [28,29]. We present two experiments, and each experiment has two cases, as shown in Fig. 7.

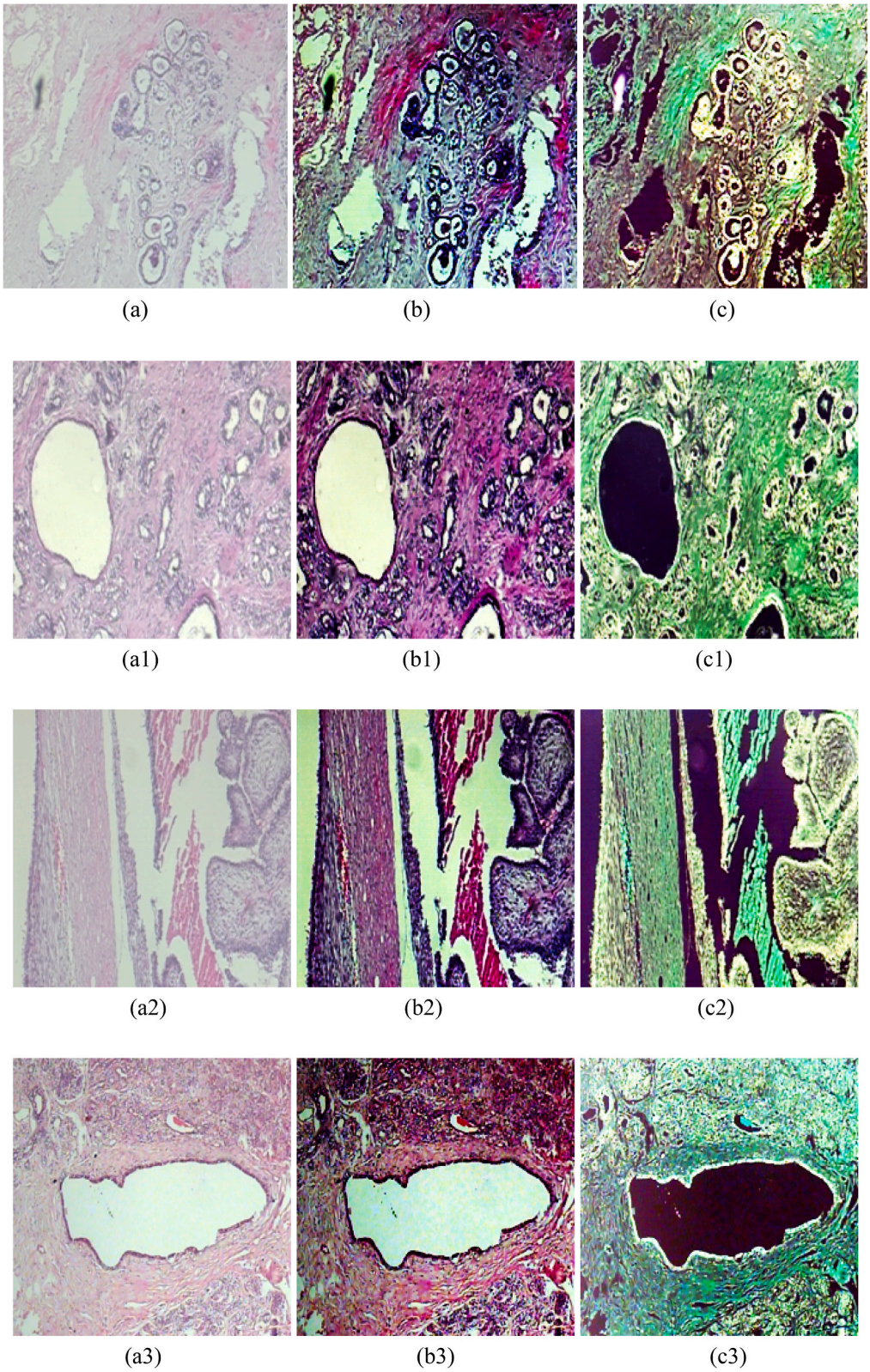


**Fig. 5.** Samples of the breast cancer images to (dataset 2) [29] in (a) and enhanced image with histogram equalization in (b) enhanced image with Complement in (c).

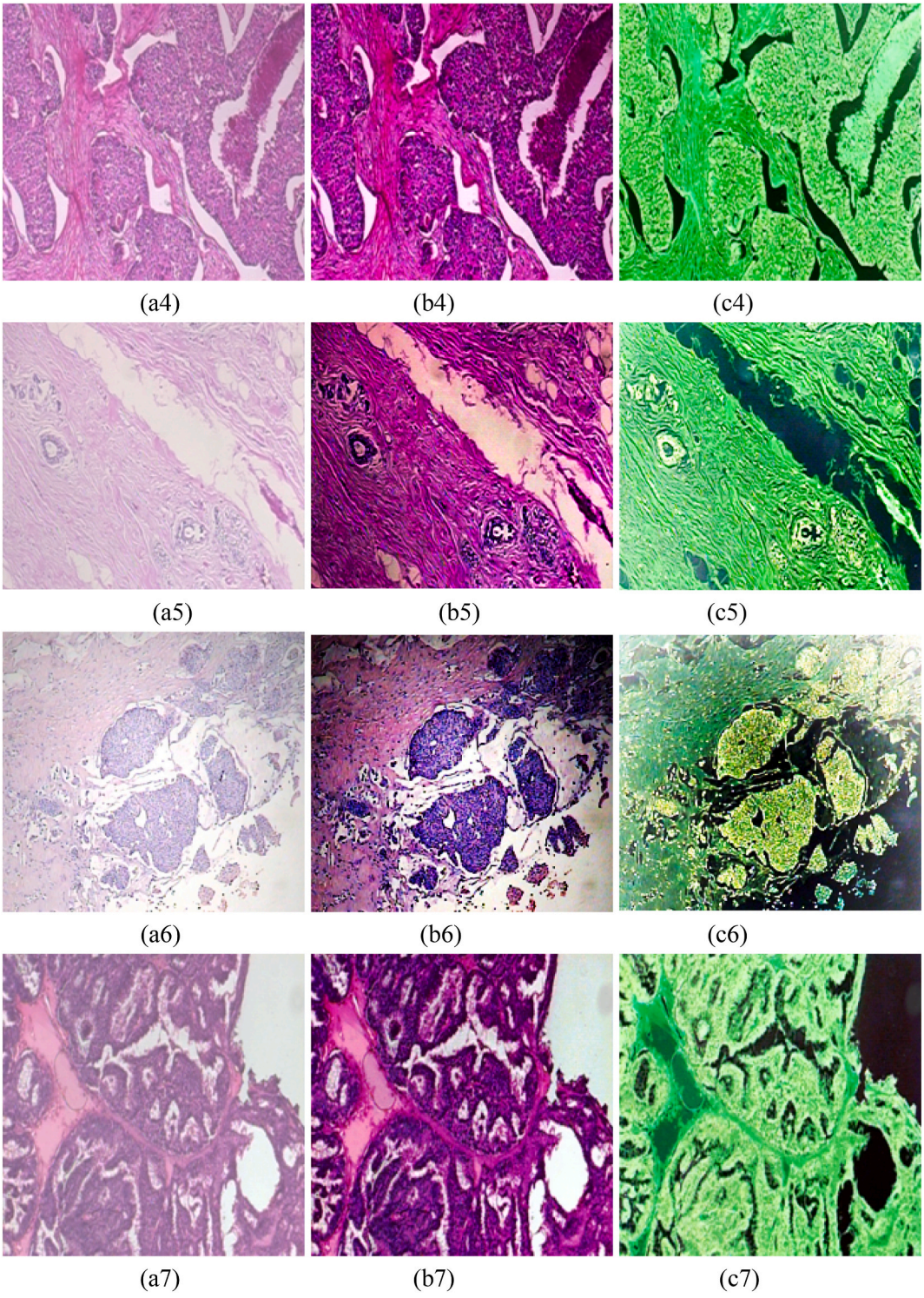


**Fig. 5.** (*continued*).

In deep learning experiments, the training phase involves the acquisition of knowledge by the model from the training dataset. This is accomplished through the adjustment of the model's parameters using an optimization algorithm, such as the Adam optimizer, and a designated loss function, such as categorical cross-entropy. The training process typically consists of iteratively processing the dataset multiple times, known as epochs, and updating the model's parameters after each iteration. In order to evaluate the performance of the

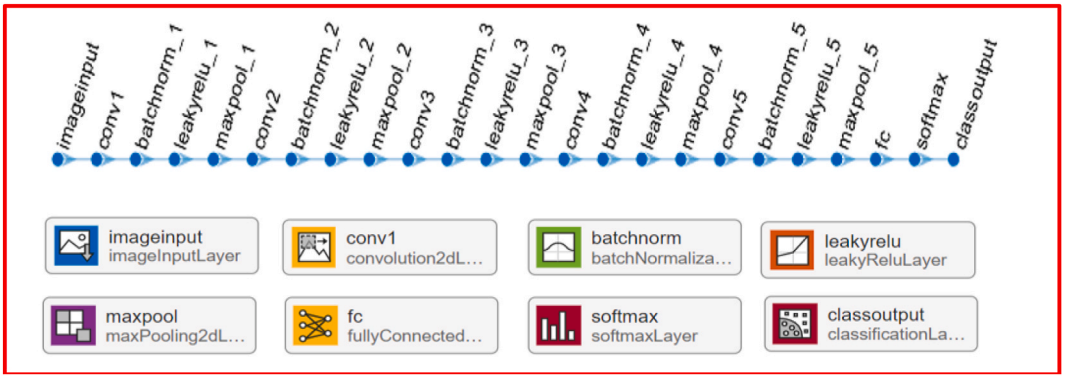


**Fig. 6.** Architecture of the designed LWCNN.

**Table 1**
Details of the proposed LWCNN model.

| Name of layer | Decimation | # Of Filter | Padding | Stride |
|---|---|---|---|---|
| Input | 224 224 3 | | | |
| Conv1 | 3 3 | 8 | Same | |
| batch normalization | | | | |
| leaky Relu | 0.01 | 1 | | |
| max pooling | 2 2 | | | 2 2 |
| Conv2 | 3 3 | 16 | Same | |
| batch normalization | | | | |
| leaky Relu | 0.01 | | | |
| max pooling | 2 2 | | | 2 2 |
| Conv3 | 3 3 | 32 | Same | |
| batch normalization | | | | |
| leaky Relu | 0.01 | | | |
| max pooling | 2 2 | | | 2 2 |
| Conv4 | 3 3 | 16 | Same | |
| batch normalization | | | | |
| leaky Relu | 0.01 | | | |
| max pooling | 2 2 | | | 2 2 |
| Conv5 | 3 3 | 8 | Same | |
| batch normalization | | | | |
| leaky Relu | 0.01 | | | |
| max pooling | 2 2 | | | 2 2 |
| Fully Connect | 2 | | | |
| Softmax | 0 or 1 | | | |
| **Classification-1** | **0, 1 (2-class)** | | Dataset-1 | |
| **Classification-2** | **0, ..., 7 (8-class)** | | Dataset-2 | |

model and mitigate overfitting, a distinct validation set is utilized during the training process. After each epoch, the model's performance on the validation set is assessed. Early stopping may be implemented as a technique to halt training if the model's performance fails to improve over a predefined number of epochs, often referred to as the patience parameter. Once the training phase is finalized, the performance of the model is assessed using an independent test dataset. This dataset is separate from both the training and validation sets, thereby enabling an unbiased evaluation of the model's ability to generalize to unseen data. Performance metrics, such as accuracy, precision, recall, or F1 score, are commonly utilized to quantify the model's effectiveness in extrapolating patterns to previously unseen data [32].

In the first experiment, the suggested classifier, there are 1240 samples for each class and a total of 2480 datasets recovered from the training dataset. Each class derives from about 992 BC pictures, and 248 are used for the validation phase in addition to 32 minimum batch sizes. The low-complexity CNN model's training phase involved the processing of these pictures. Ten epochs are used in the CNN model with a training time of around 16 min for all datasets. With 124 iterations per epoch, our maximum number of iterations is 1240. The performance information for the test results (1) for Dataset-1 and enhancement Dataset-1. As seen in Fig. 8 Accuracy and loss curves without image enhancement. Fig. 9 which Confusion matrix of training (a) and testing (b) results without image enhancement., Fig. 10, Accuracy and loss curves with image enhancement. Fig. 11 which show Confusion matrix of training (a) and testing (b) results with image enhancement.

In the second experiment, the suggested classifier is used. There are various samples for each class, and a total of 9109 datasets were retrieved from the training dataset. Each class was responsible for 7287 BC scans and 1822 for the validation phase, in addition to the 32 minimum batch sizes. The training phase of the simple CNN model was used to analyze these photos. For training all datasets in the

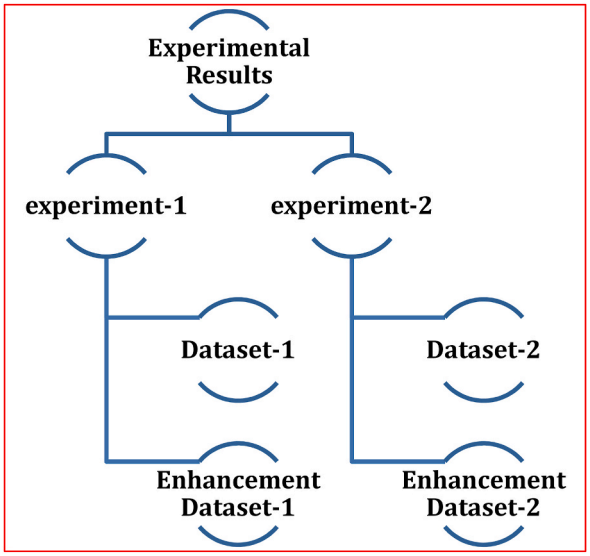


**Fig. 7.** Illustrates our experimental results steps.

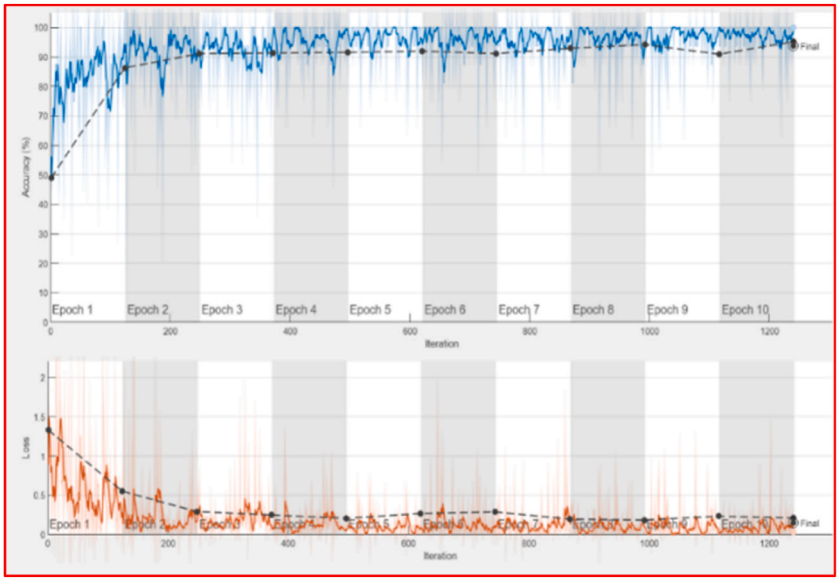


**Fig. 8.** Accuracy and loss curves without image enhancement.

CNN model, 10 epochs are used at a rate of about 16 min. So, we have a maximum of 1970 iterations and a maximum of 197 iterations each epoch. The performance information regarding the experiments for Dataset-2 and enhanced Dataset-2 As in the following:

Fig. 12 show Accuracy and loss curves without image enhancement, Fig. 13 Confusion matrix of training (a) and testing (b) results without image enhancement, Fig. 14, Accuracy and loss curves with image enhancement, and Fig. 15 show Confusion matrix of training (a) and testing (b) results with image enhancement.

In this study, the performance of the model is evaluated using a set of commonly employed metrics, namely accuracy, sensitivity, specificity, and precision [32,33]. These metrics are widely used in the field and are defined as follows in equations (1)–(5). The corresponding results are presented in Tables 2–5.

$$\text{Accuracy} = \frac{TN + TP}{TP + FP + TN + FN} \tag{1}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{2}$$

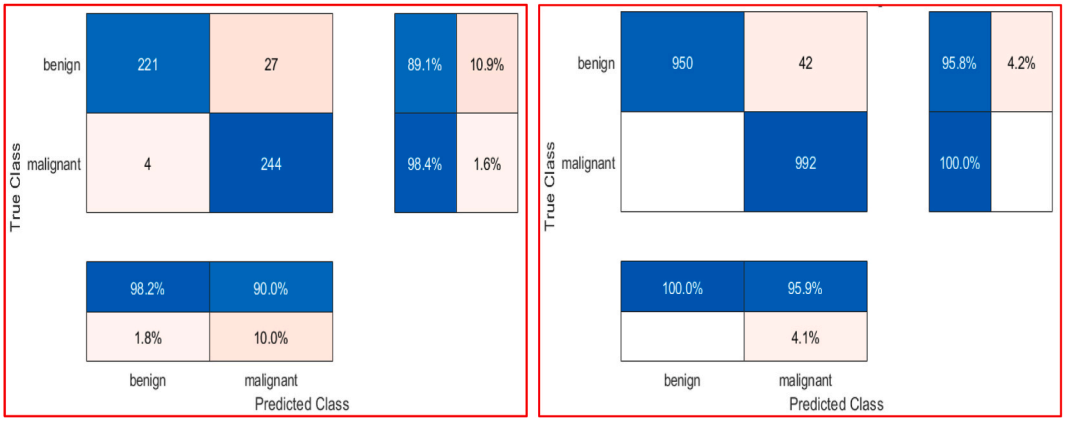


**Fig. 9.** Confusion matrix of training (a) and testing (b) results without image enhancement.

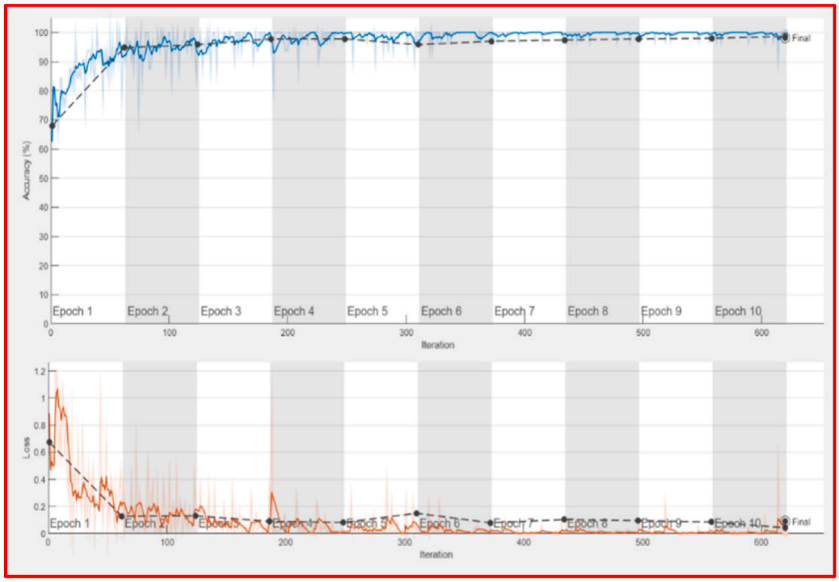


**Fig. 10.** Accuracy and loss curves with image enhancement.

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{3}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4}$$

$$F\_measure = \frac{2\ (precision * sensitivity)}{precision + sensitivity} \tag{5}$$

## 5. Discussion

The first and second experiments differ in terms of the characteristics of the datasets used such as dataset size, class distribution, and validation set size. In the first experiment, the dataset consisted of 2480 samples, evenly distributed with 1240 samples for each class. On the other hand, the second experiment employed a larger dataset with 9109 samples. The significant disparity in size indicates that the second experiment had a more extensive dataset for training and evaluation. Moreover, in the first experiment, the class distribution was balanced, meaning that there were an equal number of samples for each class. Each class contained

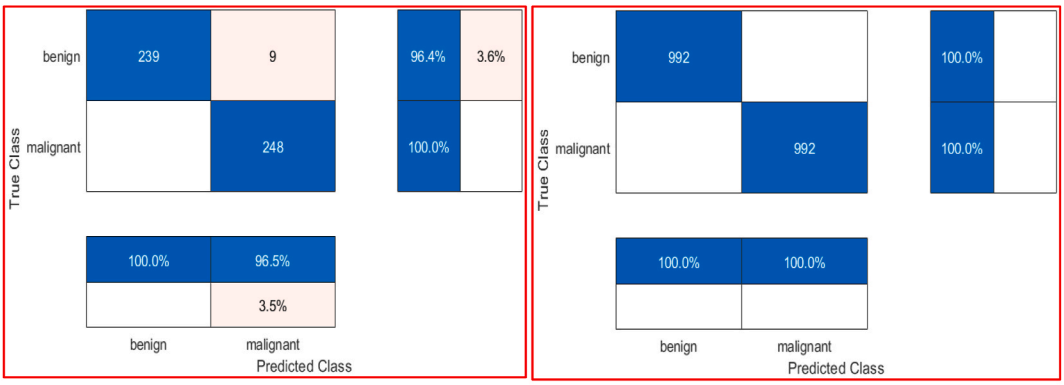


**Fig. 11.** Confusion matrix of training (a) and testing (b) results with image enhancement.

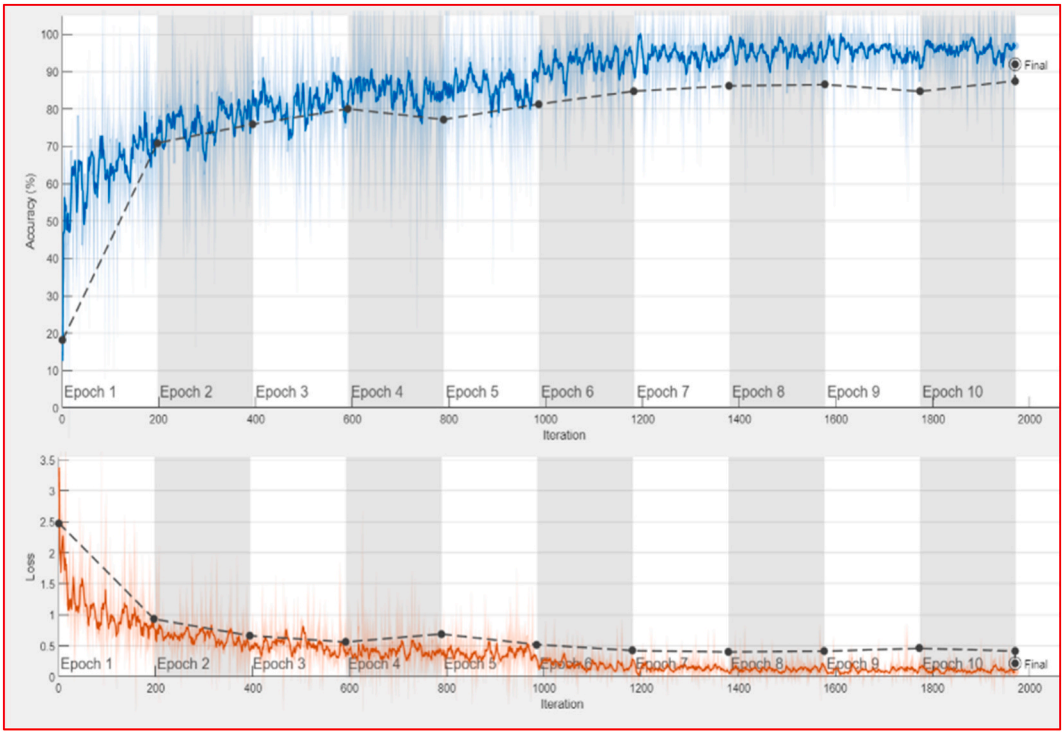


**Fig. 12.** Accuracy and loss curves without image enhancement.

approximately 992 BC pictures. In contrast, the second experiment involved an imbalanced dataset. While the exact distribution was not specified, it was mentioned that there were varying numbers of samples for each class, with each class consisting of 7287 BC scans. In addition, for model evaluation during training, both experiments utilized a validation set. In the first experiment, 248 samples were dedicated to the validation set. In the second experiment, 1822 samples were allocated for validation. This indicates that the second experiment had a larger validation set, allowing for a more comprehensive assessment of the model's performance during training. However, both experiments employed a minimum batch size of 32 during the training phase. The batch size determines the number of samples processed together in each iteration of the training algorithm.

The differences in dataset characteristics between the two experiments highlight the diversity of the datasets used. The first experiment had a smaller, balanced dataset, while the second experiment utilized a larger dataset with imbalanced class distribution. These variations can impact the model's training dynamics, the generalization ability of the classifier, and the performance evaluation metrics. By conducting experiments with different dataset characteristics, researchers can gain insights into the model's behavior and performance under various data conditions.

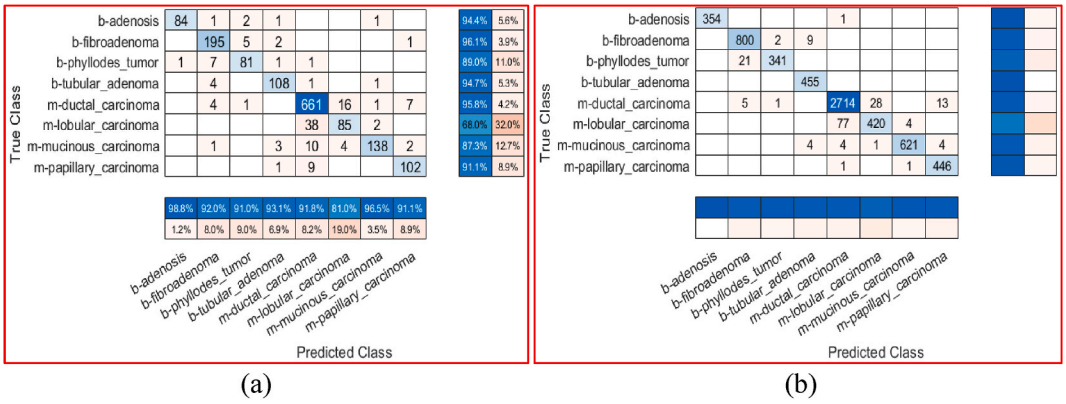


**Fig. 13.** Confusion matrix of training (a) and testing (b) results without image enhancement.

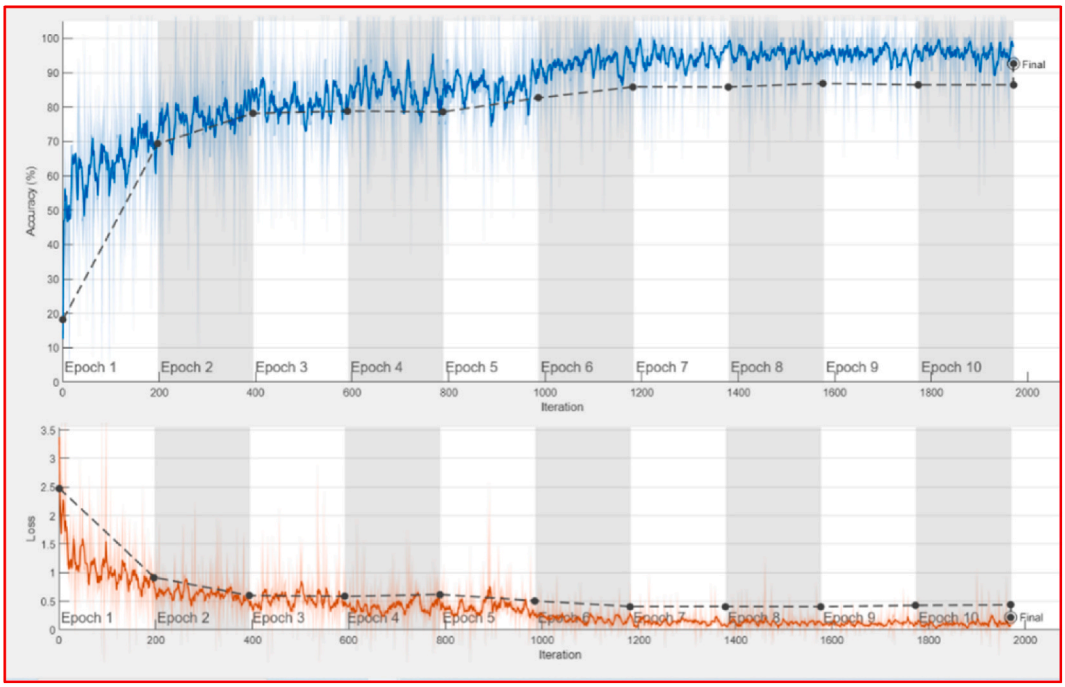


**Fig. 14.** Accuracy and loss curves with image enhancement.

## 6. Conclusion

Breast cancer is a prevalent form of cancer that extensively impacts women on a global scale. It is a serious condition that can be life-threatening if not detected and treated early. Screening mammography plays a crucial role in the timely detection of breast cancer, offering a valuable tool for early diagnosis. A screening mammogram is an X-ray procedure that is used to detect breast cancer before any symptoms are noticeable. During the screening mammography, the breast is compressed between two plates, and an X-ray is taken to produce images of the breast tissue. These images can show lumps, calcifications, or other abnormalities that may indicate the presence of breast cancer. In medical image analysis, deep convolutional neural networks (CNNs) are frequently utilized. We designed an approach for breast cancer classification using LWCNN. Classification accuracy is improved by using enhancement techniques as a preprocessing step. Without any dataset augmentation, the results supported the comparison of two trials. In the first experiment, the model was tested with two cases' original and enhancement datasets 1. It achieved 95 %, 93 %, 99 % and 98 % for training and testing accuracy respectively. In the second experiment, the model has been tested with two cases' original and enhancement datasets 2. It achieved 95 %, 91 %, 99 % and 92 % for training and testing accuracy respectively. From the experimental results, the conclusion of this work is the dataset preprocessing contributed to enhancing the classification output. Future work may involve developing more effective methods and including several datasets that have been approved by the World Health Organization. Additionally, a

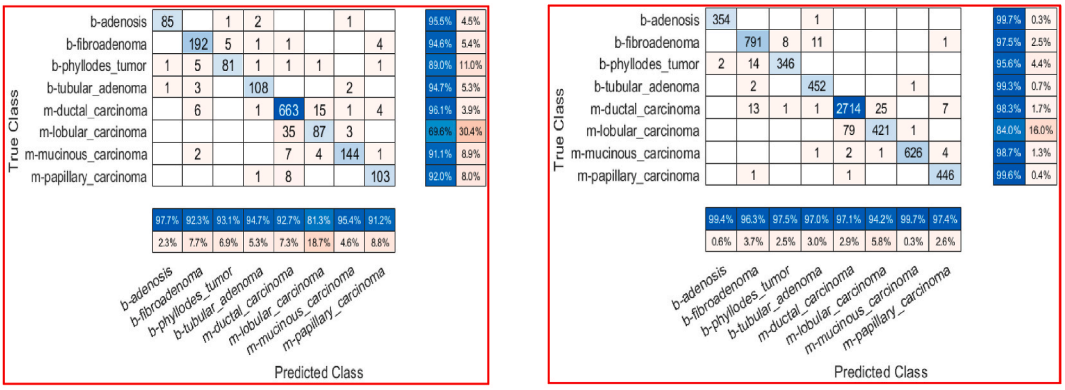


**Fig. 15.** Confusion matrix of training (a) and testing (b) results with image enhancement.

**Table 2**
The training results of the LWCNN model proposed framework. experiment-1 (Dataset-1).

| LWCNN | Ac | Pr | Se | Sp | Fm |
|---|---|---|---|---|---|
| Benign | 98 | 100 | 96 | 100 | 98 |
| Malignant | 98 | 96 | 100 | 100 | 98 |

Accuracy%(Ac), Precision%(Pr), Sensitivity%(Se), Specificity%(Sp), F_ measure%(Fm).

**Table 3**
The training results of the LWCNN model proposed framework. experiment-1 (Enhancement Dataset-1).

| LWCNN | Ac | Pr | Se | Sp | Fm |
|---|---|---|---|---|---|
| Benign | 100 | 100 | 100 | 100 | 100 |
| Malignant | 100 | 100 | 100 | 100 | 100 |

**Table 4**
The training results of the LWCNN model proposed framework. experiment-1 (Dataset-2).

| LWCNN | Ac | Pr | Se | Sp | Fm |
|---|---|---|---|---|---|
| ***b-adenosis*** | 100 | 100 | 100 | 100 | 100 |
| ***b-fibroadenoma*** | 99 | 97 | 99 | 100 | 98 |
| ***b-phyllodes_tumor*** | 100 | 99 | 94 | 100 | 97 |
| ***b-tubular_adenoma*** | 99 | 97 | 91 | 100 | 94 |
| ***m-ductal_carcinoma*** | 100 | 100 | 100 | 100 | 100 |
| ***m-lobular_carcinoma*** | 99 | 94 | 97 | 100 | 95 |
| ***m-mucinous_carcinoma*** | 100 | 99 | 100 | 100 | 100 |
| ***m-papillary_carcinoma*** | 100 | 96 | 100 | 100 | 98 |

**Table 5**
The training results of LWCNN model proposed framework. experiment-1 (Enhancement Dataset-2).

| LWCNN | Ac | Pr | Se | Sp | Fm |
|---|---|---|---|---|---|
| ***b-adenosis*** | 100 | 99 | 100 | 100 | 100 |
| ***b-fibroadenoma*** | 99 | 96 | 98 | 99 | 97 |
| ***b-phyllodes_tumor*** | 100 | 97 | 96 | 100 | 96 |
| ***b-tubular_adenoma*** | 99 | 94 | 91 | 100 | 94 |
| ***m-ductal_carcinoma*** | 97 | 100 | 97 | 98 | 97 |
| ***m-lobular_carcinoma*** | 99 | 94 | 98 | 100 | 96 |
| ***m-mucinous_carcinoma*** | 100 | 97 | 100 | 100 | 100 |
| ***m-papillary_carcinoma*** | 100 | 100 | 99 | 100 | 98 |

comprehensive system might be developed to speed up data analysis and aid medical professionals in the early diagnosis of breast cancer.

## Data availability statement

The dataset supporting the conclusions of this article is included within the article.

## CRediT authorship contribution statement

**Ahmed Elaraby:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization. **Aymen Saad:** Writing – original draft, Visualization, Validation, Software, Resources. **Hela Elmannai:** Project administration, Methodology, Investigation, Funding acquisition, Formal analysis. **Maali Alabdulhafith:** Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Myriam Hadjouni:** Visualization, Validation, Software, Resources, Funding acquisition, Data curation. **Monia Hamdi:** Resources, Project administration, Investigation, Formal analysis, Data curation.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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