An Improved Breast Cancer Detection Based on Convolutional Neural Networks with An Attention Mechanism

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ABSTRACT

Breast cancer can effectually be treated through its early detection. As such, the availability of proper screening methods is important for detecting the initial symptoms of breast cancer. Various imaging techniques are used for the screening to identify this disease, the popular ones of which include: mammography, ultrasound, and thermography. This project proposes a model using ResNet50 Convolutional Neural Network to detect breast cancer from mammograms, using Convolutional Block Attention Module (CBAM) as an attention mechanism. A varying number of blocks is used to check for optimality, among which the most optimal was identified. Experimental results on MATLAB 2021a show that the proposed model attains the most optimal performance for the case of 12 CBAM blocks with a less overfitting rate. Thus, this suggests that by reducing the number of CBAM blocks, the model can attain an optimal performance without compromising the training and testing accuracies, proving the assertion made by previous research. Further study will employ a regularization technique to address overfitting

Keywords: *Convolutional Block, Attention Module, Deep Learning and Optimization*

1. INTRODUCTION

Mammography, a technique that uses X-rays to detect malignant tumors on breasts, has emerged as an alternative to breast self-examination and is being commonly used in the medical field. Human interpretation of mammograms, however, has a high risk of false positives which often lead to unnecessary biopsies and surgeries, and false negatives which lead to delayed discovery, and subsequently unfeasibility of treatment. (Sony et al., 2021). The main purpose of mammography is to detect early signs of cancer and to diagnose breast masses from the images. Mammograms are considered the most important tools doctors have not only to screen for breast cancer, but also to diagnose, evaluate, and follow up with people who have had breast cancer. Screening with mammography is performed in two steps. First, the breast is compressed between two small flat plates. Then, a low X-ray dose is applied directly through the breast and acquired by a two-dimensional (2D) panel detector. Research shows that even the most skilled physicians can detect cancer with at most 79% accuracy, while 91% correct diagnosis is achieved using machine learning techniques (Bhinder et al., 2021).

Medical technologies power-driven by Artificial intelligence (AI) are evolving rapidly with fascinating advancements and amazing promises, reshaping medical practice today and making huge differences in human health. Convolutional Neural Networks, also referred to as the workhorse for image classification is currently the most popular deep learning practice for detecting and classifying images in cancer, bringing along momentous contributions, and having added benefits of scalability and automation when compared to human experts (Bhinder et al., 2021).

Cancer remains the leading cause of death worldwide, (Ramirez, Chiu, Hererra, Mostavi, & Ramirez, 2020) with breast cancer as the most prominent cause of cancer deaths (Alanazi et al., 2021). According to the world Health Organization (WHO) Global cancer observatory chat (Figure 1), in Nigeria, among the ten most common cancers, breast cancer is the most frequently occurring, and has the highest mortality rate among women (WHO, 2021). To a weighty extent, breast cancer is avoidable, detectable and expectantly treatable (Assegie, 2020). Contrary to what people believe, breast cancer is curable and detecting it at the earliest stages of development provides the best chances for curing it. (Biancovilli et al., 2021).

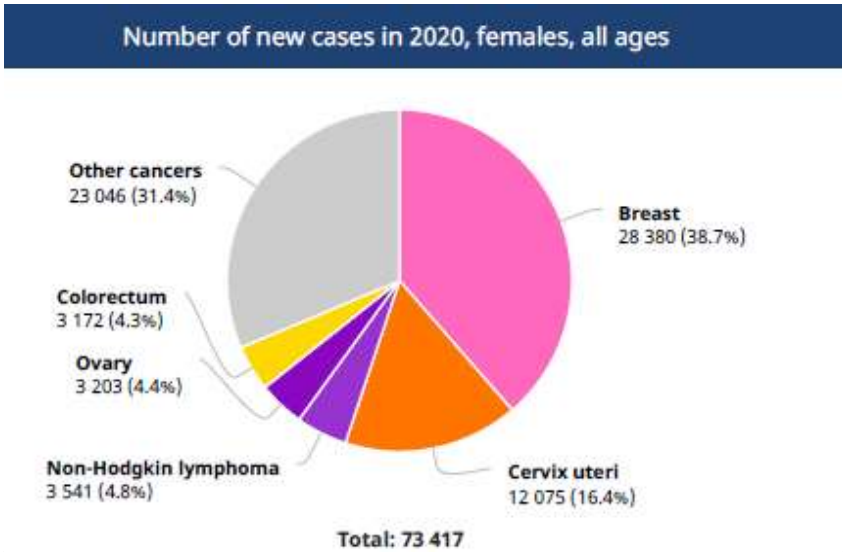

Figure 1: Number of New Cases in 2020 Source: Global cancer observatory (2021).

Convolutional Neural network mimics the working of the human brain in processing data for use in objects recognition and detection, decision making, speech recognition and language translation. CNN works by passing information from one layer of neurons to the next. (Todt & Krinski, 2019). It gets this name from mathematical linear operation between matrixes called CONVOLUTION. The CNN has an excellent performance in machine learning problems, especially the applications that deal with image data, such as image classification data set (ImageNet), computer vision, and in natural language processing (NLP).
CNN models are data-driven and can be trained end-to-end. They enable the integration of feature extraction, feature selection, and malignancy prediction into an optimization process. Thus, these retrieved features are not designed by human engineers but are cultured from the input data (Zou et al., 2019). Hence, in this study, we employed an improved version of CNN to detect cancer at its early stages. The remainder of this article is organized as follows: section 2 presents the related work; section 3 presents the method and section discuss the findings. Finally, section 5 concludes the study and proffers further study.

2. RELATED WORK

Cancer has for long been believed to be incurable. But the reality is that it is usually detected at a stage that is rather too late to be treated. Breast cancer is more consenting to treatment when discovered early. Unlike normal body cells, breast cancer cells are loosely connected and can separate easily and spread to neighboring lymph nodes, become metastases and cause danger to life. Breast cancer can even spread further to other body parts such as the lungs.(Jamal et al., 2019). For this reason, early diagnosis is necessary. Also, there are high rates of misinterpretations of mammograms in breast cancer diagnosis as many women are reported positive, when they are negative (false positive), and vice versa (false negative). Moreover, breast cancer diagnosis is faced with a lot of difficulties as the pathological images are hard to define, and, distinguishing breast cancer cells from other cells is a very tedious task, even to the most experienced doctors. Furthermore, some very minor regions can be missed (Alanazi et al., 2021).
Liang et al. (2019) proposed a model that uses Convolutional Neural Network to identify breast cancer in histopathological images by integrating Convolutional Block attention Module (CBAM) to focus on important parts of feature maps. 16 CBAM modules were used and separately inserted into different layers of ResNet50 CNN. The model however tends to overfit, so the authors suggested that future work starts by reducing CBAM blocks proportion. Furthermore, the existing study uses ADAM to optimize the parameters during training. However, Adam optimizer can suffer a weight decay problem (Kurz et al., 2022).
In a recent study, (Alanazi et al., 2021) proposed a CNN approach for the automatic diagnosis of breast cancer by examining the IDC tissue regions in Whole Slide Images. In the paper, three different CNN architectures have been

described and compared. The proposed system using 5-layer ResNet101 CNN Model on skit-learn machine learning framework. All are dataset of about 275,000, 50 × 50-pixel RGB image patches. The model was found to effectively obtain correct diagnostic results.

(Chen, 2019) proposed a CNN classifier base on image bit-plane slicing to improve recognition accuracy of breast cancer images classification. Each texture image is disintegrated into eight bit-plane images. Different bit-planes provide different levels and detail of image texture feature. The feature classification performance by each bit-plane is also tested respectively and the fusion of all bit-planes. CNN classifier was used for classification and recognition. The simulation results on the breast cancer image datasets show that the proposed method on some bit-plane can significantly improve recognition rate and promote classification accuracy.

(Yang et al., 2021) implemented a fully automatic deep learning method using Mask Regional Convolutional Neural Network (R-CNN) for detection of breast cancer by searching the entire set of images. The major limitation was the small case number and the unbalanced data. Also, the dataset used in training the model vary from the dataset used in testing the model (trained on non–fat-sat Images and tested on fat-sat Images).

Gao et al. (2018) presented a shallow-deep CNN (SD-CNN) for lesion detection and classification for contrast-enhanced DMs (CEDM). A 4-layered shallow-deep CNN was used to extract the visualization mappings of the convolutional layer in the CEDM images and combine them with low-energy (LE) images. This virtual enhancement improved the quality of LE images. ResNet was applied to these virtual combined images to extract the features to classify benign and normal cases. Using the SD-CNN on the CEDM images resulted in a significant improvement in classification accuracy compared with DMs.

3. RESEARCH METHODOLOGY

This research proposes system that uses ResNet50 Convolutional Neural Network with attention mechanism to identify breast cancer from images of breast tissues. Convolutional Neural network mimics the working of the human brain in processing data for use in objects recognition and detection, decision making, speech recognition and language translation. CNN works by passing information from one layer of neurons to the next. (Todt & Krinski, 2019).

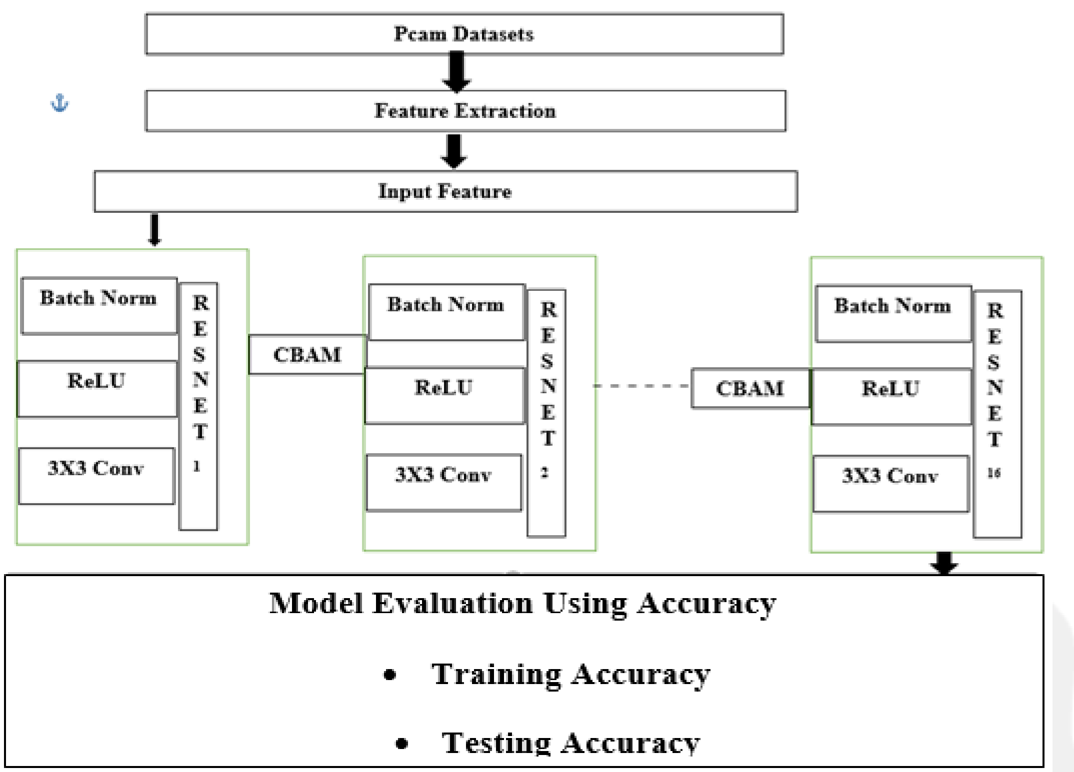

Figure 2: Setup for the Proposed Model

Convolutional Block Attention Modules (**CBAM**) are added to the layers of a CNN Model to extract the importance of different areas, or channels, of the feature maps, and weight these areas, or channels, using the importance. The research starts by reducing the proportion of the CBAM blocks in the Network as suggested by (Liang et al., 2019). However, removing the convolutional blocks from the network tends to degrade the performance of the model, as the accuracy of the model continued to reduce with every block removed. Hence, if reducing the blocks results in a decrease in accuracy, or does not handle the overfitting, other 'regularization' technique can be involved to eliminate the overfitting., while maintaining the reasonable number of convolutional blocks. Dropout has the effect of temporarily transforming the network into a smaller one, and we know that smaller networks are less complex and less prone to overfitting.

3.4 Data Collection and Choice of Metric

The dataset will be obtained from PatchCamelyon (PCam), removing any duplicate images. A total of 220,025 images were imported, out of which 250 images were removed as outliers in the preprocessing step. In each fold, 197,798 images were used for training and 21,977 images for the validation. Each image is labelled with a binary tag to indicate the presence or absence of metastatic cells. The PCam's dataset uses 10x under-sampling to enlarge the visual field, which gives the resultant pixel resolution of 2.43 microns. According to the data description, a positive label means that at least one tumor cell pixel in the center area (32 x 32px) of the image. Tumor tissue in the outer region of the patch does not influence the label. The evaluation metric used in this study is accuracy. This evaluation metric use in the study is mathematically computed as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \qquad \text{… (3)}$$

3.6 Experimental Setup and System Requirement

The proposed Model is a 50-layer ResNet Convolutional Neural Network with 16 CBAM blocks for efficient feature extraction. A CBAM block is added after each residual block as a soft attention mechanism to infer the attention map of feature maps so that two modules are connected sequentially, and the output of Res Block is used as the input of CBAM Block.

4. RESULT

After experiments on dataset, this section presents the detection rate for the proposed model on the cancer datasets as compared to other state of the art techniques. As stated earlier, the high proportion of CBAM blocks in the existing model tends to make the model to overfit. Overfitting in CNN can be detected by the difference between the accuracy of training dataset and the testing accuracy. Table 1 presents the detection rate base on four different CBAM architecture. The number of CBAM blocks were tested at 4, 8, 12 and 16 blocks respectively.

Table 1: Performance of the proposed model base on varying CBAM blocks

	Number of CBAM Blocks	**Training Accuracy (%)**	**Test Accuracy (%)**	**Overfitting rate (%)**
1	4	94.65	94.33	0.32
2	8	95.87	95.22	0.65
3	12	96.29	96.16	0.13
4	16	99.85	98.12	1.73

This research starts by reducing the proportion of the CBAM blocks in the Network as suggested by (Liang et al., 2019). Hence, we tested for varying CBAM blocks to assess if reducing the blocks might affect the accuracy while handling the overfitting. In this case from table 1. It was noticed that reducing the CBAM blocks have great effect on both the accuracy and fitting of the model. The result is plotted in Figures 3 for more intuitive explanation on how the trend continues.

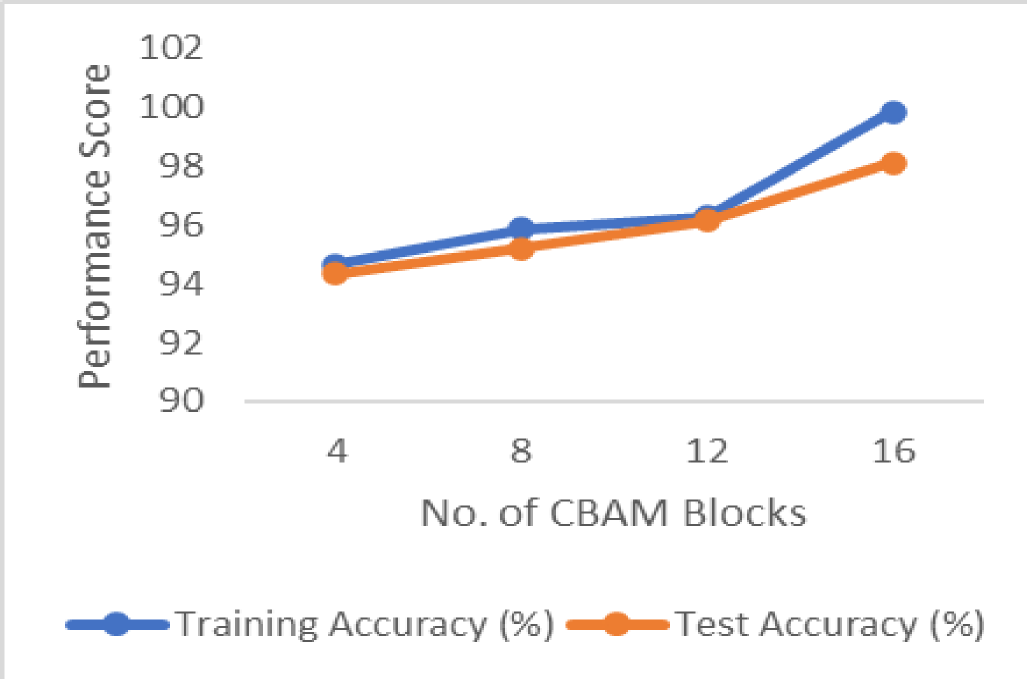

Figure 3: Performance of the Proposed Model in Terms of CBAM Blocks and Accuracies

From figure 5, reducing the CBAM blocks has significantly resulted to low training accuracy and testing accuracy respectively. Thus, as the number of CBAM Blocks was reduced to 4, 8, 12 and 16, the proposed model attains a training and testing accuracy of (94.65 % and 95.87%), (96.29% and 99.85%), (94.33 % and 95.22 %) and (96.16% and 98.12%) respectively. This clearly shows that higher CBAM blocks are associated to higher training and testing accuracy. However, to ensure the generalization of the model, we further assess the fitting abilities of the model as the number of CBAM blocks was reduced from 16 to 4. Figure 4 depicts the fitting of the proposed model base on varying number of CBAM blocks.

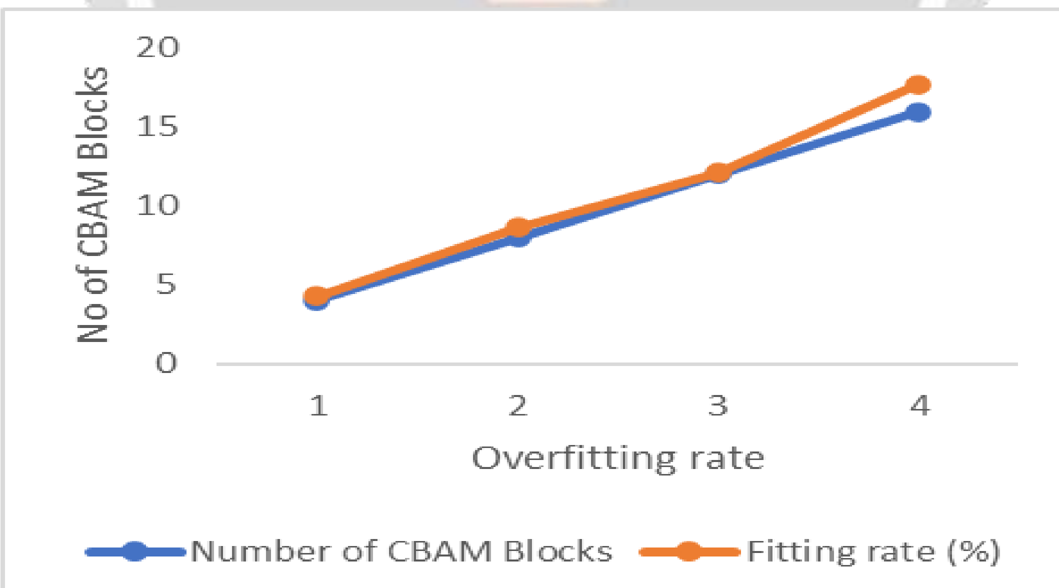

Figure 4: Performance of the Proposed Model in terms of CBAM Blocks and Overfitting Rate

From Figure 4 above, the proposed model tends to overfit as the number of CBAM blocks were increase in the architecture, thus having the highest overfitting rate with 16 CBAM blocks architectural settings. However, it was also observed that the proposed model attains the most optimal performance for the case of 12 CBAM blocks with less overfitting rate. Thus, this suggest that by reducing the number of CBAM blocks, the model can attain an optimal performance without compromising the training and testing accuracies, proving the assertion made by previous researches.

4. CONCLUSIONS

A deadly and aggressively spreading disease like breast cancer deserves a capable approach to its early and accurate detection. This early detection has been proven as the only way to completely cure breast cancer. This research targets the faults associated with breast cancer screening by introducing the Convolutional block attention Mechanism into ResNet-50 Convolutional Neural Networks in the screening of mammograms so that cancerous cells can be detected even at their earliest stages development. Experimental results on MATLAB 2021a shows that the proposed model attains the most optimal performance for the case of 12 CBAM blocks with less overfitting rate. Thus, this suggest that by reducing the number of CBAM blocks, the model can attain an optimal performance without compromising the training and testing accuracies, proving the assertion made by previous researches. Further study will employ a regularization technique to address overfitting. We will further compare the classification performance of the proposed study with other state of the art approaches using AOC, Precision and recall.

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