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# A Convolutional Neural Network Approach for Deep Learning-based Breast Cancer Detection

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**ABSTRACT**

Early and accurate breast cancer (B) diagnosis is crucial for improving patient outcomes and survival rates, which currently range from 30% to 50%. Deep learning has emerged as a powerful tool in healthcare, particularly for analyzing large volumes of medical images like X-rays, MRIs, and CT scans. This study introduces a novel deep learning model, BCNN, designed to detect and classify breast cancers into Three distinct categories: malignant lobular carcinoma, malignant mucinous carcinoma, and malignant papillary carcinoma. The BCNN model was developed and compared against two fine-tuned, pre-trained models which is VGG16, MobileNet initially trained on the ImageNet database. Breast cancer MRI images, sourced from a Kaggle dataset, were used for training and evaluation. To enhance the dataset's size and diversity, a Generative Adversarial Network technique was employed for data augmentation. The dataset included images at four different magnifications (40X, 100X, 200X, and 400X), along with a combined dataset. Each model, including the proposed BCNN, was evaluated across all five datasets, resulting in a total of 30 experiments. Performance was assessed using F1-score, recall, precision, and accuracy metrics. The experimental results demonstrated the effectiveness of the proposed BCNN model, achieving a classification F1-score accuracy of 99.38%. The fine-tuned pre-trained models also performed well, with the following F1-score accuracies: VGG16 produce 97.67%), and MobileNet Produce 97.38%). The study concluded that data augmentation, preprocessing, and balancing significantly improved the performance of both the BCNN model and the fine-tuned pre-trained models. Notably, the highest accuracies were observed when using the 400X magnification images, likely due to their superior resolution.

***Keywords:*** *Breast cancer, BCCN, VGG16, MobileNet, MRI*

## 1. INTRODUCTION

Breast cancer arises when breast cells grow uncontrollably, forming tumors that can become life-threatening if they spread beyond the breast. The cancer typically originates in the milk ducts or lobules, and while early-stage, in situ cancer is often not life-threatening, it can progress to invasive cancer, spreading to nearby tissues and potentially metastasizing to distant organs. Metastatic breast cancer is particularly dangerous and can be fatal. Treatment strategies are tailored to the individual, the specific cancer type, and the extent of its spread, often involving a combination of surgery, radiation therapy, and medication.Globally, breast cancer remains a significant health concern. In 2022, there were an estimated 2.3 million new cases diagnosed in women and 780,000 deaths. Although breast cancer can affect women of any age after puberty, it is more prevalent in later life. Significant disparities in breast cancer burden exist across different levels of human development. In high HDI countries, the lifetime risk of diagnosis is 1 in 12, with a mortality rate of 1 in 71. Conversely, while the diagnosis rate is lower in low HDI countries (1 in 27), the mortality rate is significantly higher (1 in 48), highlighting the impact of access to early detection and treatment.While breast cancer predominantly affects women (99% of cases), men can also develop the disease (0.5-1%). Treatment principles for male breast cancer are generally the same as for women. Several risk factors are associated with breast cancer, including increasing age, obesity, alcohol consumption, family history, radiation exposure, reproductive history (age at menarche and first pregnancy), tobacco use, and postmenopausal hormone therapy. However, it's important to note that approximately half of all breast cancers occur in women with no identifiable risk factors other than being female and over 40. Although family history increases risk, most women diagnosed with breast cancer do not have a known family history. The absence of a family history does not necessarily indicate a lower risk.

## 2. LITERATURE REVIEW:

### *2.1. Understanding breast cancer as a global health concern.*

Breast cancer is now the most commonly diagnosed cancer in the world. The most recent global cancer burden figures estimate that there were 2.26 million incident breast cancer cases in 2020 and the disease is the leading cause of cancer mortality in women worldwide. The incidence is strongly correlated with human development, with a large rise in cases anticipated in regions of the world that are currently undergoing economic transformation. Survival, however, is far less favorable in less developed regions. There are a multitude of factors behind disparities in the global survival rates, including delays in diagnosis and lack of access to effective treatment. The World Health Organization's new Global Breast Cancer Initiative was launched this year to address this urgent global health challenge. It aims to improve survival across the world through three pillars: health promotion, timely diagnosis, and comprehensive treatment and supportive care. In this article, we discuss the key challenges of breast cancer care and control in a global context.

### *2.2 Deep Learning in Breast Cancer Imaging: State of the Art and Recent Advancements in Early 2024*:

he rapid advancement of artificial intelligence (AI) has significantly impacted various aspects of healthcare, particularly in the medical imaging field. This review focuses on recent developments in the application of deep learning (DL) techniques to breast cancer imaging. DL models, a subset of AI algorithms inspired by human brain architecture, have demonstrated remarkable success in analyzing complex medical images, enhancing diagnostic precision, and streamlining workflows. DL models have been applied to breast cancer diagnosis via mammography, ultrasonography, and magnetic resonance imaging. Furthermore, DL-based radiomic approaches may play a role in breast cancer risk assessment, prognosis prediction, and therapeutic response monitoring. Nevertheless, several challenges have limited the widespread adoption of AI techniques in clinical practice, emphasizing the importance of rigorous validation, interpretability, and technical considerations when implementing DL solutions. By examining fundamental concepts in DL techniques applied to medical imaging and synthesizing the latest advancements and trends, this narrative review aims to provide valuable and up-to-date insights for radiologists seeking to harness the power of AI in breast cancer care.

### *2.3 Machine learning and new insights for breast cancer diagnosis:*

Breast cancer (BC) is the most prominent form of cancer among females all over the world. The current methods of BC detection include X-ray mammography, ultrasound, computed tomography, magnetic resonance imaging, positron emission tomography and breast thermographic techniques. More recently, machine learning (ML) tools have been increasingly employed in diagnostic medicine for its high efficiency in detection and intervention. The subsequent imaging features and mathematical analyses can then be used to generate ML models, which stratify, differentiate and detect benign and malignant breast lesions. Given its marked advantages, radiomics is a frequently used tool in recent research and clinics. Artificial neural networks and deep learning (DL) are novel forms of ML that evaluate data using computer simulation of the human brain. DL directly processes unstructured information, such as images, sounds and language, and performs precise clinical image stratification, medical record analyses and tumour diagnosis. Herein, this review thoroughly summarizes prior investigations on the application of medical images for the detection and intervention of BC using radiomics, namely DL and ML. The aim was to provide guidance to scientists regarding the use of artificial intelligence and ML in research and the clinic.

### *2.4 Deep learning approaches for breast cancer detection in histopathology images:*

Breast cancer is one of the leading causes of death in women worldwide. Histopathology analysis of breast tissue is an essential tool for diagnosing and staging breast cancer. In recent years, there has been a significant increase in research exploring the use of deep-learning approaches for breast cancer detection from histopathology images. To provide an overview of the current state-of-the-art technologies in automated breast cancer detection in histopathology images using deep learning techniques. This review focuses on the use of deep learning algorithms for the detection and classification of breast cancer from histopathology images. We provide an overview of publicly available histopathology image datasets for breast cancer detection. We also highlight the strengths and weaknesses of these architectures and their performance on different histopathology image datasets. Finally, we discuss the challenges associated with using deep learning techniques for breast cancer detection, including the need for large and diverse datasets and the interpretability of deep learning models.Deep learning techniques have shown great promise in accurately detecting and classifying breast cancer from histopathology images. Although the accuracy levels vary depending on the specific data set, image pre-processing techniques, and deep learning architecture used, these results highlight the potential of deep learning algorithms in improving the accuracy and efficiency of breast cancer detection from histopathology images.

## 3. METHODOLOGY:

### *Deep Learning Models used in all of the Experiments:*

Two deep learning models were employed in this study: the proposed BCNN model and two established pre-trained models,VG G16, MobileNet. These pre-trained models are widely recognized and frequently used in deep learning research.

### *3.1 VGG16:*

The pre-trained VGG16 model served as a feature extractor in this study. Developed by Karen Simonyan and Andrew Zisserman of the Visual Geometry Group Lab at Oxford University, VGG16 achieved notable success, winning the ILSVRC 2014 competition. Its appeal lies in its uniform architecture, accepting input images of a fixed 224x224x3 dimension. The architecture comprises multiple blocks of convolutional and max-pooling layers, culminating in a dense classifier that produces 1000 class scores. VGG16 is a large CNN architecture, boasting 138 million trainable parameters due to the extensive number of neurons in its fully connected layers. Training VGG16 from scratch can be computationally intensive and time-consuming. However, leveraging transfer learning, we utilized VGG16 with pre-trained weights for efficient feature extraction.

### *3.2 MobileNet:*

MobileNet, a 53-layer deep convolutional neural network, is designed for efficient and computationally lightweight mobile vision applications. Its applications span various real-world tasks, including object detection, fine-grained classification, facial attribute recognition, and localization. While other models exist, MobileNet distinguishes itself through its relatively low computational resource requirements. The overall MobileNet architecture and (B) a detailed explanation of the Depth-wise Separable (DS) convolution layer.

### *3.3 The proposed model (BCNN) :*

The proposed model, named Breast Cancer Convolutional Neural Network (BCNN), is an 18-layer CNN designed for breast cancer classification. It accepts input image dimensions ranging from 48x48 to 224x224 pixels. BCNN's distinguishing feature is its efficient use of hyperparameters. It primarily employs 3x3 convolutional filters with a stride of 1 and utilizes the same padding, coupled with 2x2 max-pooling filters with a stride of 2. This consistent arrangement of convolution and max-pooling layers is repeated throughout the architecture, as depicted in Figure 3. The network concludes with a fully connected layer followed by a softmax output. This relatively large architecture contains approximately 21 million parameters. To ensure unbiased model performance, class balance was maintained within each dataset. The datasets were partitioned into training, validation, and testing sets using a 60:20:20 split. The four individual magnification datasets (40X, 100X, 200X, and 400X), each containing 10,000 images, were divided into 6,000 training images, 2,000 validation images, and 2,000 testing images. The combined dataset (Complete Dataset), comprising 40,000 images, was similarly split into 24,000 training images, 8,000 validation images, and 8,000 testing images.

## 4. EXPERIMENTAL SETUP AND RESULTS:

All experiments were conducted using a Google Colab online lab environment. Each virtual machine was configured with a gaming motherboard, 8 GB of RAM, and 60 GB of hard disk space. This configuration facilitated the completion of all experimental iterations, with an average runtime of approximately 2 hours per test. illustrates the structure of the 30 experiments performed in this study. The experimental scenario. Initially, all six deep learning models were trained using the 40X dataset (first six experiments). Subsequently, the 100X dataset was used (second six experiments), followed by the 200X dataset (third six experiments), the 400X (fourth six experiments), and finally, the combined "Complete Dataset" (40X, 100X, 200X, and 400X) in the last six experiments.The proposed BCNN model and the Two pre-trained models were trained for 120 epochs. To mitigate overfitting, the first 60 epochs incorporated data augmentation, while the subsequent 60 epochs were conducted without augmentation, recognizing the potential for overfitting with the dataset size. Identical hyperparameters were used for training and validation across all models to ensure a fair performance comparison and determine the optimal model for breast cancer classification. During training, loss and accuracy metrics were recorded for subsequent comparative analysis.

***Training accuracies of all models across the five Events.***

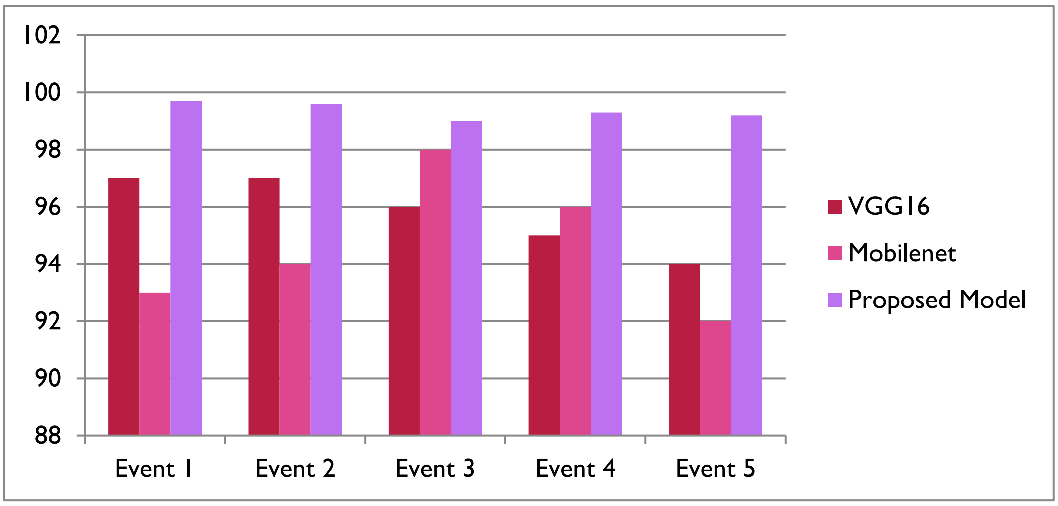


**Figure:1**

Each experiment utilized a unique dataset, categorized by image magnification. Four magnifications (40X, 100X, 200X, and 400X) were used, with each magnification constituting a separate dataset. A fifth dataset, termed "All Datasets Together," combined all magnifications. This approach allowed for a comparative analysis of performance across datasets, evaluated using F1-score, recall, precision, accuracy, and training, validation, and testing times. For each dataset, five pre-trained deep learning models were fine-tuned for breast cancer detection and classification. Additionally, a novel deep learning model, BCCNN, was developed for the same purpose.

***Training loss of all models across the five events.***

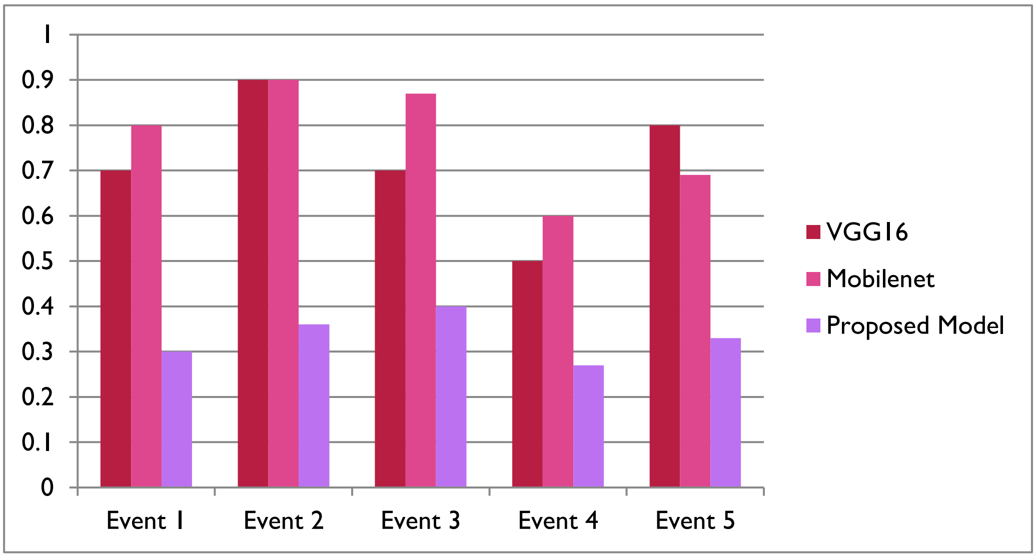


**Figure 2**

All models were trained, validated, and tested on each dataset, and the results were recorded. This section compares the performance of each dataset (experimental scenario) against the others.Across all scenarios, training accuracy for the six models approached 99%. However, the highest validation accuracies were achieved by the proposed model (97.89%) and one other model (98.59%). The proposed model also demonstrated the highest testing accuracy (97.80%), closely followed by VGG16 (97.66%). The lowest training loss was observed with the proposed model (0.0035), followed by VGG16 (0.0092). For validation loss, VGG16 achieved the lowest value (0.03355), with the proposed model exhibiting the second lowest (0.0585). Similarly, VGG16 had the lowest testing loss (0.00036), followed by the proposed model (0.00672). Regarding time performance, MobileNet was the fastest (1.7 seconds), followed by the proposed model (2.9 seconds). The proposed model also achieved the highest precision (98.39%) and recall (99.38%), followed by VGG16 (97.67% for both).

Consequently, the proposed model achieved the highest F1-score (99.28%), again followed by VGG16 (97.65%). Based on these

***Time Performance of All models in the 5 Events***

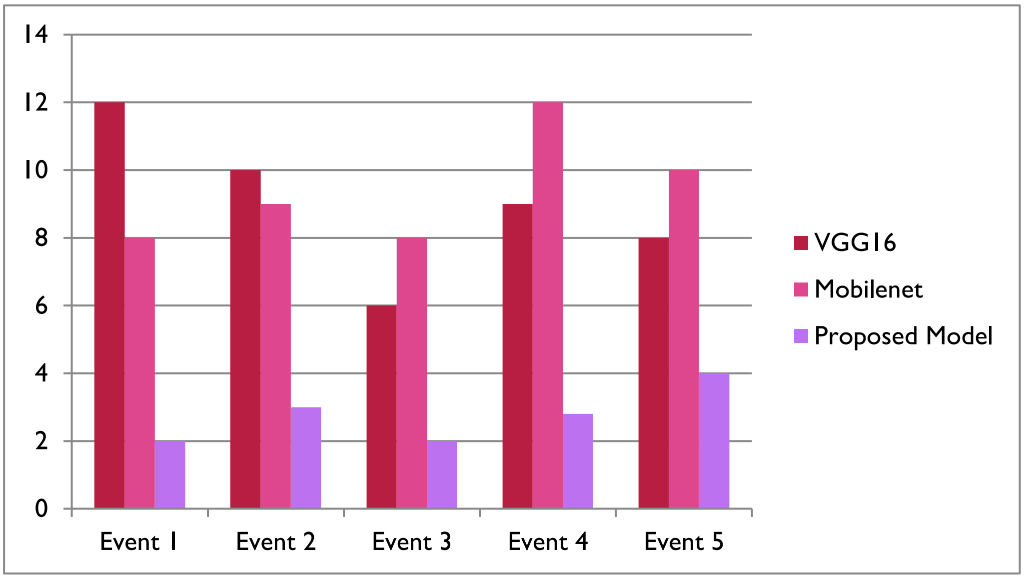


***Figure 3***

performance metrics (precision, recall, F1-score, and time), the proposed BCCNN model appears to be the most effective.

## 5. CONCLUSION:

This study investigated breast cancer detection and classification using various datasets (40X, 100X, 200X, 400X, and a combined dataset). Dataset balancing was performed, and the performance of a proposed deep learning model was evaluated against Two pre-trained models VGG16,MobileNet. The proposed BCNN model achieved the highest accuracy (99.38%), recall (99.30%), precision (99.39%), F1-score (99.28%), and exhibited strong time performance (1.7 seconds). The best results were obtained in the fourth scenario, utilizing the 400X dataset. These promising results suggest potential applicability in diverse human-computer interaction domains.

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