

## A DEEP LEARNING VGG16 ARCHITECTURE OF CNN TO DETECT THE BREAST CANCER

Mrs.N.Harini<sup>1</sup>, Lekkala Sai Laxmi<sup>2</sup>, Mounika Nannapaneni<sup>3</sup>, Kanchustambham Anjali Pravallika<sup>4</sup>,  
Kattumuri Mounika<sup>5</sup>, K S S Venkata Sri Varshini<sup>6</sup>

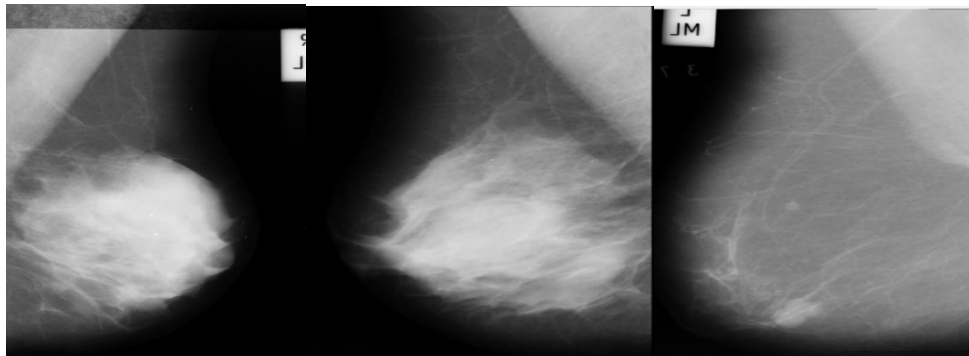
Department of Computer Science and Engineering, Vignan's Institute of Engineering for Women, Visakhapatnam, India.

### ABSTRACT

Breast cancer is currently the most prevalent and significant cause of death among women. In comparison to other cancer types, breast cancer is considered the second highest level of expected deaths in women with 14% in 2016. Recently, it has represented a serious health problem worldwide with the highest rate of 29% among other kinds of cancer. Moreover, the number of women diagnosed with breast cancer in 2016 reached 2,46,660. Moreover, Breast cancer early detection plays a major role in the diagnosis and the treatment options, and it leads to a 5-year survival rate of 97.5%. In contrast, when the diagnosis is delayed and cancer spreads to other organs, the patient has a 5-year survival rate of only 20.4%. Globally, there were 6,84,996 breast cancer-related deaths in 2020(WHO,2021).Breast cancer early detection continues to be a major problem throughout the world. Due to the high performance achieved in image classification, deep learning technologies are currently becoming a buzzword, especially for breast histopathology imaging applications, such as diagnosis.Among deep learning types, Convolutional Neural Networks (CNN) are the most common types of deep learning models utilized for medical image diagnosis and analysis. Unfortunately, CNN has a significant implementation computation cost and may need a large number of parameter adaptations. Several pre-trained models have been developed with the predetermined network architecture in order to handle this issue. This study uses a transfer learning model based on the Visual Geometry Group with a 16-layer deep model architecture to extract high-level features (VGG16).

### INTRODUCTION

Breast cancer continues to be one of the most serious public health issues, and it is the main reason why women die from cancer around the world. Hence, to prevent the effects of the disease's progression and lower its morbidity rates in women, early diagnosis of the condition is essential. Breast cancer cells encompass a variety of entities with unique clinical and histological characteristics. Figure 1 shows two rows of images; the top row shows benign cells images while the bottom row show malignant cells ones. Regrettably, this cancer develops from the growth of abnormal breast cells and has the potential to spread to nearby healthy organs.



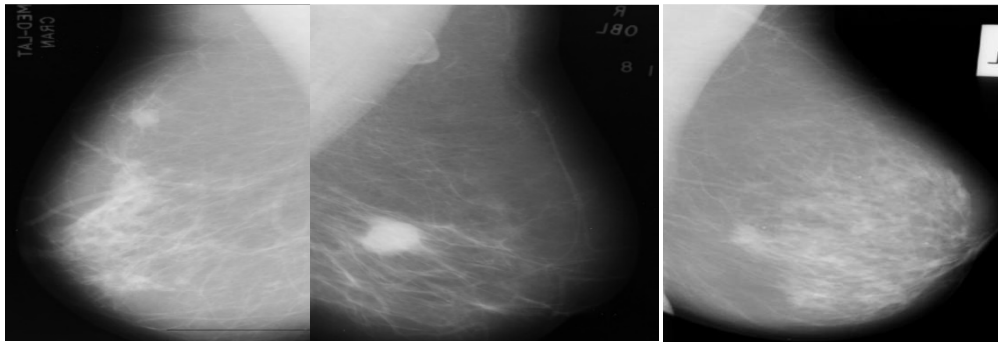


Figure 1: Breast histopathology images, top row: benign, bottom row: malignant.

Several methods are used in the clinical diagnosis of breast cancer. The first method uses radiological pictures such as magnetic resonance imaging (MRI), mammography, and others to do clinical screening. But non-invasive imaging won't be effective in locating the malignant spot. Thus, to analyze the malignancy professionally, biopsy images are used with different stained to produce histopathology images. Unfortunately, manual analysis of the histopathological images is laborious, time-consuming, and dependent on the expertise of the physician. Thus, manual diagnosing is subjective. In order to accomplish this, Computer-Aided Diagnosis (CAD) is a crucial tool for pathologists to use while examining the histopathological images and identifying the suspicious area. Typically, it increases the diagnostic performance of breast cancer by reducing the inter-and intra pathologist variation in making a final decision.

Images from the malignant pathology are frequently analysed using a variety of machine learning approaches.. The most common analysis models for digital histopathology image analysis are CAD systems. The previous studies on breast CADs can be divided into shallow machine learning and deep learning. The input/training images are primarily utilised to extract features for the shallow machine learning CADs, which are subsequently used to train a classifier (e.g. SVM). Therefore, these models are sometimes categorized as Handcrafted features based models.

Some drawbacks of these conventional CADs are that: first, the quality of the CADs depends on the extracted features, however extracting representative features from a picture is a highly challenging task. Second, the inter- and intra-class variation in the histopathology pictures may not be appropriate for using acquisition characteristics. Third, most of the extracted features are based on class label information (supervised); thus, they can be lying to biased results.

As opposed to the traditional CADs, which were based on the features that were extracted, DL is crucial in multiple classification tasks and can achieve high performance and extract high-level features from histopathology images automatically. To mitigate conventional CADs practices limitations, numerous recent scholars thought of entrusting classification tasks to deep learning models, which can be adapted to select the most powerful features based on conventional and pooling layers.

For the categorization of histopathological breast pictures, CNN-based feature extraction models have gotten the most attention from academics among DL models. This study has two main goals: First, the pre-trained deep learning VGG16 as a feature extractor for breast cancer histopathology image classification will be examined in this work. Second, this study investigates the capability of three different classifiers for classifying the extracted features of breast histopathology images. The three classifiers are ResNet101, mobileNetV2 and visual geometry group(VGG16).

## LITERATURE SURVEY

This section provides details about the previously completed research's associated work. In essence, there are two methods utilised to detect breast cancer. There are many researches that are conducted using the machine learning. But machine learning techniques have some problems that are removed through the deep learning. This section gives the information about machine and deep learning techniques.

1. Zhou X, Li C, Rahaman MM, Yao Y, Ai S, Sun C, et al "A Comprehensive Review for Breast Histopathology Image Analysis Using Classical and Deep Neural Networks"

The authors in [1] summarized the various techniques used to classify breast cancer using histopathological image analysis (HIA) based on different architectures of Artificial Neural Networks (ANN). The authors *Artificial Intelligence in Medicine*, Elsevier, Vol 127, May 2022 grouped their work according to the applied dataset. They arranged it in ascending chronological order. This work found that ANNs were first used in the field of HIA around 2012. ANNs and PNNs were the most frequently applied algorithms. However, in feature extraction, most of the work used textural and morphological features. It was clear that Deep CNNs were quite effective for early detection and diagnosis of breast cancer, leading to more successful treatment. Prediction of Non-Communicable Diseases (NCDs) was conducted using many algorithms.

**2. Wisesty UN, Mengko T, Purwarianti A** “Gene mutation detection for breast cancer disease”

On the other hand, the authors in [2] focused on gene mutation for detecting breast cancer. A genetic mutation is a change to a gene's DNA sequence to produce something different. It creates a permanent change to that gene's DNA sequence. Genetic variations are important for humans to evolve, which is the process of change over generations. They mentioned that the gene prediction classification phase aims to carry out gene annotation, gene finding and gene mutation detection to ascertain the presence or absence of a cancer. They concluded that several methods can be used including regression, probability models, SVMs, NNs and deep learning. They also mentioned the many opportunities available to capture the relationship between nucleotide and feature extraction, since DNA sequencing involves a large amount of data in the form of a string sequence.

**3. Mahmood M, Al-Khateeb B, Alwash WM** “A review on neural networks approach on classifying cancers”

In [3], the authors demonstrated the effectiveness of NNs in the classification of cancer diagnoses, especially in the initial stages. A neural network is a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates. In this sense, neural networks refer to systems of neurons, either organic or artificial in nature. Neural networks, also known as artificial neural networks (ANNs) or simulated neural networks (SNNs), are a subset of machine learning and are at the heart of deep learning algorithms. Their name and structure are inspired by the human brain, mimicking the way that biological neurons signal to one another. According to their study, the majority of neural networks have shown promise in detecting tumor cells. However, the imaging approach requires high computational capacity to preprocess the images.

**4. Fatima N, Liu L, Hong S, Ahmed H** “Prediction of Breast Cancer, Comparative Review of Machine Learning Techniques, and Their Analysis”

In [4], the authors reviewed different machine learning, deep learning and data mining algorithms related to breast cancer prediction. Several research papers on breast cancer were reviewed, with a total of 27 papers in machine learning, 4 papers in ensemble techniques and 8 papers in deep learning techniques. Ensemble methods are techniques that create multiple models and then combine them to produce improved results. Ensemble methods usually produces more accurate solutions than a single model would. This has been the case in a number of machine learning competitions, where the winning solutions used ensemble methods. The authors mentioned that most of the papers used imaging, while only a few papers used genetics. The main algorithms used to predict breast cancer using genetics were SVM, decision tree and random forest. However, imaging techniques used several algorithms such as CNNs and Naïve Bayes.

**5. Pang T, Wong JHD, Ng WL, Chan CS** “Deep learning radiomics in breast cancer with different modalities: Overview and future”

In [5], the authors examined recent studies applying deep learning to breast cancer with different imaging modalities. They organized these studies using the aspects of dataset, architecture, application and evaluation. They focused on deep learning frameworks developed in three breast imaging modalities (ultrasound, mammography and MRI). In their work, they attempted to provide state-of-the-art findings about breast cancer imaging utilizing DLR-based CAD systems. Their study included private datasets and classification using CNNs. After studying these surveys, our contribution will involve studying genetic sequencing and imaging at the same time to predict breast cancer and to get more information that can help

early diagnosis and treatment of breast cancer. We will also provide recommendations to researchers who wish to conduct research in this area.

## PROPOSED SYSTEM

### Deep Convolutional Neural Network

Among deep learning approaches, CNN is considered a dominant technique from deep learning approaches. It has been used in various data science tasks such as medical image classification and feature extraction from the input training images using a pre-trained CNN model. Practically, CNN tries to learn and extract high-level features which are able to discriminate between different class labels in a classification task. In most cases, the extracted features from CNN outperform the handcrafted features.

The main components of the CNN are stack of input, multiple hidden, and output layers. The foremost work is in the hidden layers, which are typically comprised of several convolutional layers (CL), pooling layers, and the last layer is set of the fully connected layers (FC). Extra layers can be added to build a complex model, which allows the model to learn more complicated features towards superior decision making. Figure 2 shows the typical CNN architecture, where the convolutional and pooling layers are used to extract features from the input training set by using a small filter (e.g., 3x3) which is sliding on the image. In CNN, each CL is used to extract the distinct set of features from an image set. For example, one CL is responsible for edges, bright spots, dark spots, shapes. In contrast, other is responsible for shapes and objects relating to the image which are recognizable. The next main layer is the pooling, which is responsible for reducing the feature map's dimensionality while preserving the most vital information, such as max and average pooling. The FC layer is called the classifier layer. After passing through the FC layers, the output layer (final layer) produces probabilities of the input based on the softmax activation function.

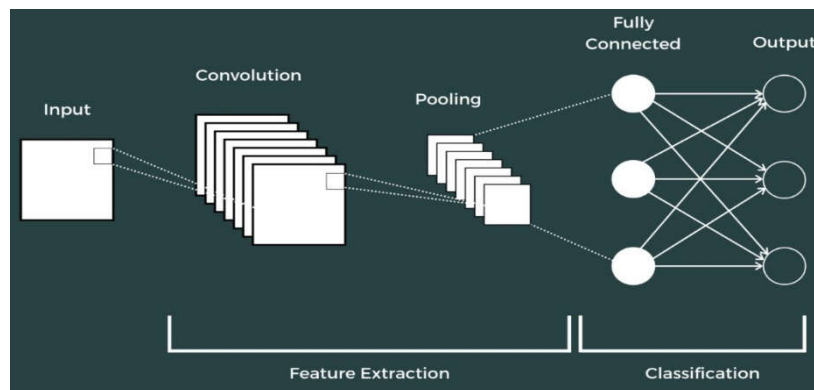


Figure2 : Layers of convolutional neural network

In recent years, CNN is growing fast, and various architectures have been introduced. One of the famous CNN is VGG16. It has less filter size comparing to other architectures and simple layer architecture. Like previous CNN models, VGG16 was pre-trained on the enormous ImageNet dataset and demonstrated for a number of image classification tasks, including the categorization of breast cancer.

### VGG16

VGG16 is one of the most common deep learning architectures. The prominent architecture for VGG16 is presented in Figure 3. It includes 41 layers disturbed as the following: 16 weight layers, 13 convolutional layers (Conv.), and 3 FC layers. VGG16 employs a small 3x3 kernel (filter) on all Conv Layers with stride one. Max pooling layers always follow Conv. Layers. The input for VGG16 is fixed 224x224 three channels images. In VGG16, the three FC layers have different depths. The last FC has 1000 channel size, which corresponds to the number of the class label in the imageNet dataset, whereas the previous two have the same channel size (4096). The output layer is the soft-max layer which is responsible for the given probability for the input image.

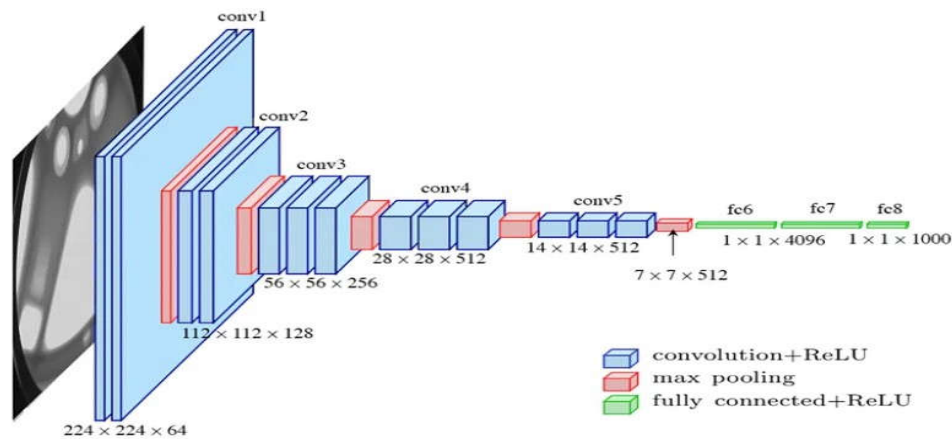


Figure 3 : VGG16 Architecture

As any pre-trained models, VGG16 requires heavy training if the weights are initialized randomly. So, in general, CCN models utilize transfer learning (TL) techniques. TL refers to a mechanism in which a model trained on one task is utilized in some way on a second similar task. I.e., we train a CNN model on a similar problem to the problem that is being addressed, where the input is the same, but the output may be of a different in nature. In this case, the VGG 6 model is trained using the ImageNet dataset, which contains many real world object images.

Then, the weights of layers migrate to a BC classification task/ feature extraction. Thus, the training time is reduced. Besides, TL is a more powerful classification technique when a small dataset is evaluated . TL can be used either for classification or feature extraction after the adaptation of some layers from the pre-trained model. In this study, the capability of the VGG16 with transfer learning is utilized to extract high level features from the input images.

The nature of breast histopathological images carry many textures, shape, and histological structure such as nuclei, cytoplasm. In order to extract deep representative features from the input histopathology pictures, the suggested method makes use of VGG16. The main steps of the proposed method are: First, the input training images are resized to consist of the size of the input layer of the VGG16. Second, the final three levels (FC) layers (Top layers of the stack), which represent the classifier, are removed from the VGG16 to modify it for the histopathology pictures. Thus, the leaving layers are convolutional and pooling layers. The input image is passed through the model to extract 4096 features. After preparing the data by extract the features from all input images, we divide the data into training 90% and testing (10%) to be used with a set of classifiers. Then, we trained three diverse classifiers, namely resNet101, ,mobileNetV2, and Visual geometry group(VGG16).

## DATASET

In the implementation of the present study, the mini-mias dataset for breast cancer histopathology images is used. The dataset consisting of 322 images is divided into benign and malignant images. The attributes of the mias dataset includes MIAS database reference number, character of background tissue, class of abnormality present, severity of abnormality, x,y image-coordinates of centre of abnormality and approximate diameter of a circle encompassing the anomaly in pixels.

## RESULTS AND DISCUSSION

### 1) Experimental Setup

This study conveyed two main experiments with images from mias dataset. For each image, the VGG16 is used to extract 4096 features. The dataset is built using these features and the class labels for the images. This data set is divided into 90% training and 10% testing. Then, we trained three classifiers, namely resNet101, ,mobileNetV2 and Visual geometry group(VGG16).

### 2) Evaluation Methods

In this study, various metrics such as accuracy, area under curvature(AUC), and loss are applied to measure the image diagnosis performance for classification.

### 3) Results

On training the dataset with three different classifiers named resNet101, mobileNetV2 and Visual geometry group(VGG16), the results are as in the table 1.

Classifier	Accuracy	Area Under Curvature	Loss
ResNet 101	0.974	0.996	0.071
MobileNetV2	0.955	0.992	0.112
VGG 16	0.977	0.998	0.059

Table 1: Comparison of proposed model with previous deep learning approaches on the same dataset

Since the training results are pretty well with VGG16 model, we tested the dataset against the same model. The accuracy, area of curvature and loss are 0.9356, 0.9730 and 0.2356 respectively. As testing data is low, the training and testing accuracy varies a lot.

## CONCLUSION

Extracting high-level features from breast histopathological images assists in improving the effectiveness of the diagnostic process. Thus, the main objective of this study is to utilize VGG16, a pre-trained model from CNN deep learning, to extract the high-level features from breast images. To do that, we removed the last fully connected layers in VGG16. Then, the obtained features were classified using a set of classifiers. Extensive experiments on MIAS dataset (public dataset) were carried out, and a set of performance metrics was calculated for performance evaluation (on test data portion). The experimental results outperformed various techniques in the state-of-art. This demonstrate the effectiveness of the extracted features using VGG16.

## FUTURE SCOPE

**Integration with other data modalities:** While VGG16 primarily operates on image data, the future scope for breast cancer detection may involve integrating other data modalities, such as clinical data, genetic information, or radiomic features extracted from medical images. By combining multiple data sources, researchers could develop more comprehensive models that consider various aspects of breast cancer and improve accuracy.

**Multi-instance learning:** Breast cancer detection often involves identifying cancerous regions within mammograms or other medical images. Traditional CNNs like VGG16 treat the entire image as a single instance, potentially missing smaller cancerous lesions. Future research may explore adapting VGG16 or similar architectures to work with multi-instance learning approaches, where the model can identify and classify cancerous regions at a finer granularity within the image.

**Large-scale screening and real-time applications:** With the advancements in computing power and hardware, the future scope for breast cancer detection using VGG16 may involve deploying the model for large-scale screening programs or real-time applications. This could include developing efficient implementations that can process large volumes of medical images rapidly, allowing for quicker and more accurate detection of breast cancer.

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