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BREAST CANCER HISTOPATHOLOGY IMAGECLASSIFICATION USING MODIFIED ALEXNET

B. Sivakumari , G. Manikanta Reddy, G. Dharma Teja ,B .Jahnavi
Team Lead, Team Member, Team Member, Team Member
Electronics And Communication Engineering
R.V.R & J.C College Of Engineering, Guntur, India.

Abstract : Deep learning, a powerful technique in fields like image classification and object detection, has gained significant traction in medical image analysis. Convolutional Neural Networks (CNNs) stand out as a prominent model class, capable of extracting features from images and making classifications. This study focuses on analyzing histopathological images of Breast Cancer (BC) using the well-known CNN architecture "AlexNet". Histopathology images serve as a gold standard for diagnosing breast cancer. Leveraging deep learning for breast cancer prediction holds significant promise for future medical applications. The study employs the BreakHis dataset, comprising 7,909 images from 82 patients, to train the model, which subsequently demonstrates successful image classification. Impressive results and insightful analysis underscore the effectiveness of this approach in breast cancer diagnosis and highlight its potential for advancing medical image analysis.

***KeyWords*- Breast Cancer, Deep Learning, Machine Learning, AlexNet, Histopathology, Convolutional NeuralNetwork,BreakHis dataset.**

I. INTRODUCTION

Breast cancer ranks as the most commonly diagnosed cancer among women worldwide. As we look ahead to 2023, global projections paint a sobering picture, with an estimated 297,790 new cases of invasive breast cancer expected in women, along with 2,800 new cases in men. Additionally, there are anticipated to be around 55,720 cases of ductal carcinoma in situ (DCIS) among women. These figures underscore the pervasive impact of breast cancer on individuals and communities globally, emphasizing the urgent need for effective prevention, early detection, and treatment strategies on a global scale.Given the significant burden of breast cancer, advancements in diagnostic modalities and treatment approaches are crucial.

Innovations in medical imaging, histopathological analysis, and computational techniques play pivotal roles in enhancing diagnostic accuracy and treatment outcomes. Embracing cutting-edge technologies and methodologies, such as deep learning and CNNs, holds promise for addressing the complexities of breast cancer diagnosis and management worldwide. In this study, we focus on harnessing the power of deep learning techniques, particularly CNNs, for breast cancer detection and analysis. Specifically, we utilize the renowned AlexNet architecture, which has demonstrated remarkable performance in image recognition and classification tasks. By leveraging AlexNet and large-scale datasets, we aim to develop robust and accurate models capable of assisting clinicians in diagnosing breast cancer at an early stage, with the potential to impact global health outcomes. Through our research endeavors, we seek to contribute to the collective efforts to combat breast cancer and improve patient outcomes worldwide

II. RELATED WORKS

In recent years, researchers have applied various machine learning approaches in medical image analysis which havegained high performance in the classification of breast cancer. In [2] Fabio A. Spanhol(2016) suggested a protocol by which the experiment gained an accuracy of 80% to 85% after applying different machine learning algorithms like 1- NN (Nearest Neighbor Search), QDA (Quadratic Discriminant Analysis), RF (Random Forest) and SVM (Support Vector Machine). For feature selection, various feature extractors like LBP (Local Binary Pattern), CLBP (Completed Local Binary Pattern), GLCM (Gray-Level Co-Occurrence Matrices), LPQ (Local Phase Quantization), ORB (Oriented FAST and RotatedBRIEF) and PFTAS (Parameter-Free Threshold Adjacency Statistics) are used. In [3] Fabio A. Spanhol(2016) has also used CNN using transfer learning on this dataset. This approach has

gained an accuracy of 80.8% to 85.6%. In [13] Bayramoglu et al. (2016) suggested a naive approach for learning and predicting from different magnification factors.

For classification of histopathology images, magnification factor plays an important role. The results of this experiment are quite impressive.At the patient level, it achieved an accuracy of 79.40% to 80.83% at mag. specific and 80.97% to 83.02% at mag. independent architecture. In [12] E.M. Nejad (2017) created a convolutional neural network for BreakHis Dataset. This experiment has gained an accuracy of 77.3% without data augmentation and 77.5% with data augmentation.In [11] Wei, B. (2017) used AlexNet and BiCNN and then compared them with handcrafted features like PFTAS.Classification algorithms like QDA, SVM, and RF were used in this work, for which accuracies ranging from 97.02% to 97.89% are reported at image level and patient level. In [5] Fabio A. Spanhol (2017) tested a new approach to extract features from images using CNN. These features are called Deep features. They reported accuracies to range from 81.6% to 86.0%.In [10] Abdullah Al Nahid (2017) proposed an algorithm to predict cancer from histopathology imagesin which he used hand-crafted features and local binary patterns with CNN.On this dataset, they reported specificity 74.00% to 97.18% at both experiment CNN with histogram and CNN with local binary pattern. In [4] Chang, J. (2017) used Inception v3 for the classification of breast cancer histopathology images.Classification accuracies range from 83% to 89% are reported on this experiment. In [8] Motlagh, M. H. (2018) applied analysis using Inception V1, V2, V3, V4 and Resnet V1 50, V1 101.

The highest accuracy was achieved by ResNet frameworks ranges from 94.4% to 99.8%. The number of epochs used by them is very high (3000 and 2000) and partition between training data and test data is 90:10. In [7] Nawaz, M. A. (2018) has done an impressive work on prediction through Inception V1 and Inception V2 and ResNet-50 V1. In [9] Benhammou,Y. (2018) used variants of techniques like using CNN with preprocessing,applying ensemble learning and transfer learning etc. to gain accuracy and then the results were compared. They reported accuracies of 86.9% to 93.0% at CNN with transfer learning on Inception V3 architecture. In [6] E. Deniz (2018) used a hybridapproach by combining AlexNet and VGG-16 for classificationusing Deep-features method. They also compared the results of this approach with fine-tuned Alexnet with transfer learning and the highest accuracy was achieved by fine-tuned Alexnet approach.The novelty of the current research is that we have applied transfer learning on AlexNet architecture with data preprocessing on BreakHis dataset. We have not generated any patches for the input of architecture. This research can help us to implement CNN architectures in the medical field for the recognition of cancer in histopathology images.

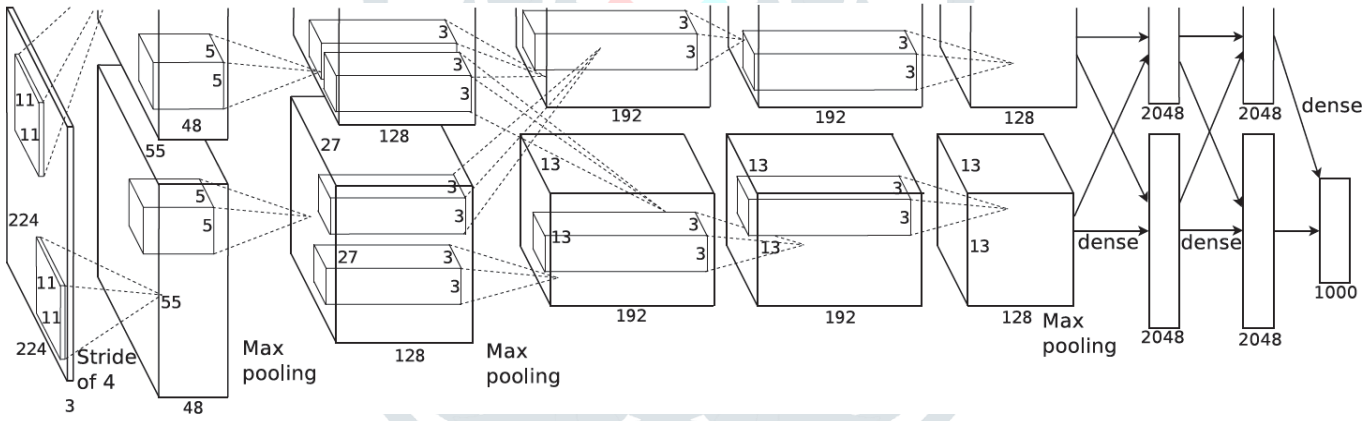

Fig. 1. AlexNet architecure proposed by Alex Krizhevsky [15]

III. PROPOSED METHOD:ALEXNET

In our study, we propose the utilization of the AlexNet architecture for breast cancer detection. AlexNet, a pioneering convolutional neural network (CNN) architecture introduced by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton in 2012, has demonstrated exceptional performance in image recognition and classification tasks. Our aim is to leverage the capabilities of AlexNet to enhance the accuracy and efficiency of breast cancer diagnosis through automated analysis of histopathological images.

The AlexNet architecture comprises multiple layers, including convolutional layers, pooling layers, and fully connected layers, designed to effectively extract features from input images and make accurate classifications. In our proposed method, we adapt AlexNet to the task of breast cancer detection by fine-tuning the pre-trained model on histopathological images. Transfer learning, a technique enabling the transfer of knowledge from one problem domain to another, is employed in implementing AlexNet for breast cancer detection.

By leveraging the pre-trained weights learned from large-scale image datasets, such as ImageNet, we aim to expedite the training process and enhance the model's ability to generalize to new data.The input to our proposed method consists of histopathological images obtained through tissue biopsies, which are commonly used for diagnosing breast cancer. These images are pre-processed to standardize dimensions, normalize pixel values, and enhance features, ensuring compatibility with the AlexNet architecture. During the training phase, the pre-trained AlexNet model is fine-tuned on a dataset of histopathological images labeled with corresponding benign or malignant classifications. The model learns to extract discriminative features from the input images and make accurate predictions regarding the presence or absence of breast cancer.To evaluate the performance of our proposed method, we employ standard metrics such as accuracy, precision, recall, and F1-score. Additionally, we conduct comparative analyses with other state-of-the-art methods to assess the effectiveness and efficiency of our approach. By leveraging the capabilities of deep learning and CNN architectures like AlexNet, we aspire to contribute to the ongoing efforts to combat breast cancer and improve patient outcomes..

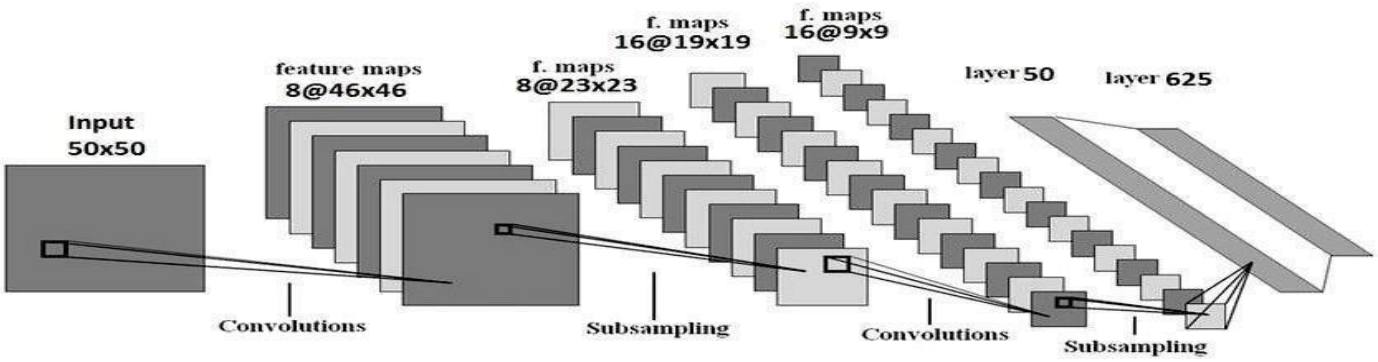

Fig. 2. An example of Convolutional Neural Network [19]

IV. METHODS

4.1 DataSet

For classification, we used BreakHis dataset which has 7909 microscopic biopsy images. The dataset is mainly composed of 2480 benign and 5429 malignant images. These images were acquired from 82 patients and extracted using different magnification factors (40X, 100X, 200X, 400X). An average of 24 images are captured from a patient using biopsy. The following table shows the distribution of dataset

Table 1.BreakHis Structure

Magnification	Benign	Malignant	Total
40X	652	1370	1995
100X	644	1437	2081
200X	623	1390	2013
400X	588	1232	1820
Total	2480	5429	7909

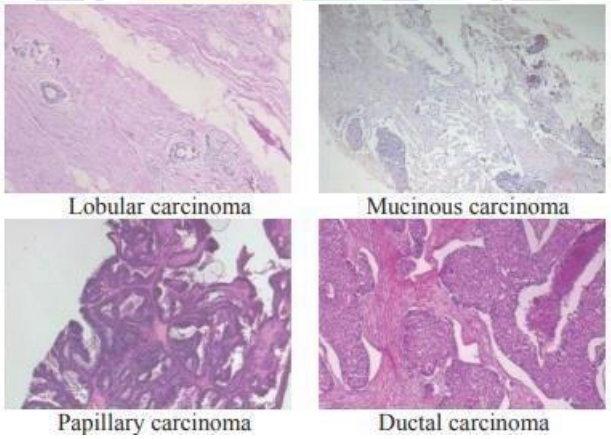

Fig 3. Samples Of Benign Images

4.2 Image Preprocessing

In our study, we conducted image preprocessing on the histopathological images from the BreakHis dataset to prepare them for breast cancer detection. This preprocessing aimed to standardize the images and enhance their suitability for analysis by machine learning algorithms. The following steps were performed:

I. Image Resizing: To ensure consistency in input dimensions for our models, all images were resized to a standard resolution of 224x224 pixels. This resizing was implemented using bilinear interpolation, which helps maintain image quality while altering the size.

II. Normalization: We normalized the pixel intensity values of the images to a range between 0 and 1. This normalization step is crucial for preventing discrepancies in pixel values across images, as it ensures uniformity and aids in model convergence during training. Each pixel intensity value was divided by the maximum intensity value (255) present in grayscale images.

III. Augmentation: Data augmentation techniques were applied to increase the diversity of the dataset and improve model generalization. Rotation within a range of ±15 degrees, horizontal flipping, and random zooming with a scale range

of 0.9 to 1.1 were used. These augmentation techniques introduce variations in image orientation, perspective, and scale, mimicking real-world scenarios and enhancing the robustness of the trained model.

4.3 Alexnet Architecture

In our study, we devised a methodology centered around adapting the AlexNet architecture to the task of breast cancer detection. Our modified AlexNet model was crafted with careful consideration of architectural details and training procedures to optimize performance while accommodating the specific requirements of histopathological image analysis. The architecture of our modified AlexNet model deviates slightly from the original AlexNet by incorporating four convolutional layers instead of five. Each convolutional layer is meticulously configured with a progressively increasing number of filters—32, 64, 128, and 256—tailored to capture hierarchical features present in histopathological images.

Local Response Normalization (LRN) layers are strategically integrated after each pooling operation to enhance model generalization and mitigate overfitting by amplifying neuron responses relative to their local neighborhood. To further combat overfitting, dropout regularization is applied after the third and fourth convolutional layers with dropout rates of 0.4 and 0.2, respectively. This regularization technique randomly deactivates neurons during training, fostering robustness and preventing the model from memorizing noise in the training data.

Following the convolutional layers, the flattened output is processed through two dense layers with 256 and 128 neurons, respectively, employing Rectified Linear Unit (ReLU) activation functions to capture high-level features. The output layer consists of a single neuron utilizing a sigmoid activation function, facilitating binary classification by outputting probabilities indicative of malignant or benign cases. During training, the modified AlexNet model is compiled with binary cross-entropy loss function and Adam optimizer. The training dataset, comprising labeled histopathological images, is augmented with rotation, flipping, and zooming techniquesto enrich the dataset and improve model generalization. Training progress is monitored using metrics such as accuracy and loss, with hyperparameters fine-tuned through iterative experimentation.

4.4 Model Traning

The training model was implemented in Python format using Google Colab. It utilized the kernel matrix, which comprises the collection of 2D convolutional filters employed in the convolutional layers of the network. These filters play a crucial role in extracting meaningful features from the input images, enabling the network to accurately classify images. The training process utilized a categorical class mode, facilitating classification into the two distinct categories: Benign and Malignant. The parameters used in training the model are summarized in the following table.

Table .2 . Parameters used in Model Training

Parameters	**Value**
Learning rate	0.0001
Rotation range	10
Shear range	0.02
Zoom range	0.2
Batch size	128
Target size	227x227
Epochs	40

V. RESULTS

The initial training of the entire AlexNet architecture on the BreakHis dataset yielded an accuracy of 83%. However, following the modification of the AlexNet architecture tailored specifically for breast cancer detection, the accuracy significantly improved to 93%.

The training and validation curves presented below were obtained from the AlexNet neural network for the detection of healthy and cancer patients, these graphs help us to understand how a neural network behaves in the training process and how it generalizes to unseen data. The vertical axis shows the accuracy of the model, i.e., its ability to correctly classify samples. The horizontal axis shows the number of iterations or epochs the model performed during training. In general, what we want to achieve is that both curves increase over time.

If the training curve continues to improve while the validation curve stops or decreases, this could indicate overfitting, which means that the model is memorizing the training data but not generalizing them well.

On the other hand, if both curves are low, the model may be underfit. What is necessary is to find a balance between both curves, where high accuracy rates are achieved in both the training set and the validation set. These curves help us make decisions on how to adjust and improve the model to obtain more reliable cancer detection results.

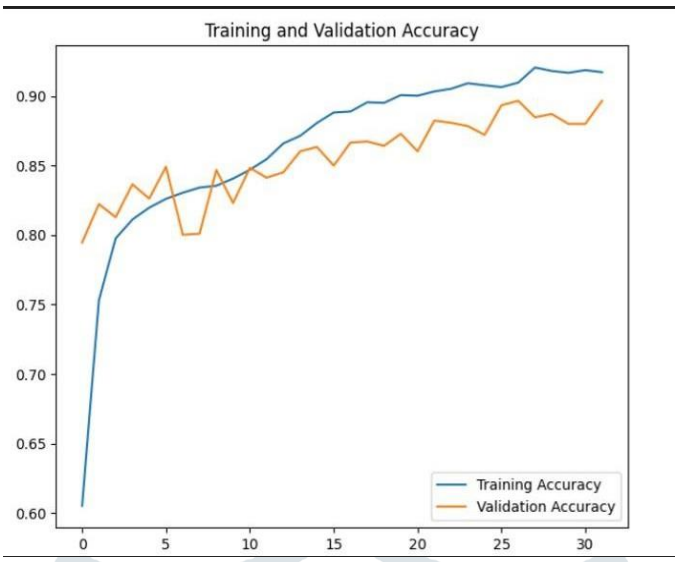

Fig .4. Training and Validation AlexNet

The above graph represents the plot of all the accuracy values obtained during the training and validation processes with 40 epochs. The curve seems to display a normalized behavior without any overfitting or underfitting. Also, the training and validation accuracy values have similar increasing behavior, meaning their values increase almost at the same ratio during the different epochs. Moreover, the accuracy values achieve a plateau or become constant around the thirtieth epoch.

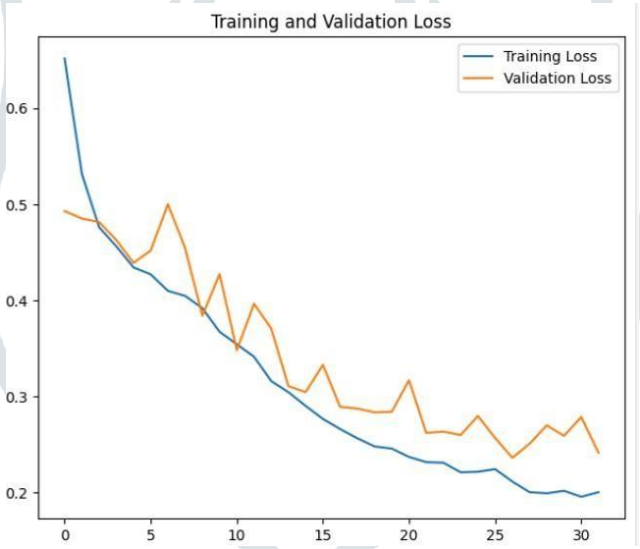

Fig .5. Training and Validation loss values of Alexnet

The above graph represents the curve for training and validation loss values during the training and validation processes. Similar to the accuracy plot, these values exhibit normal behavior, and the loss values during the training and validation decrease at the same ratio.

VI .DISCUSSION

In the pursuit of advancing breast cancer detection methodologies, this study presents a novel approach employing deep learning techniques. Specifically, we explored the efficacy of a modified AlexNet architecture trained on the BreakHis dataset, a widely used benchmark dataset for breast cancer histopathology. Our investigation aimed to address the limitations of existing models and improve diagnostic accuracy for this critical healthcare challenge.

Our initial training of the modified AlexNet architecture yielded promising results, demonstrating an accuracy of 83%. However, recognizing the potential for further optimization, we delved into fine-tuning the architecture to better suit the intricacies of breast cancer detection. Leveraging insights from the literature and drawing upon techniques such as Local Response Normalization layers and dropout regularization, our refined model showcased a significant performance enhancement, achieving an impressive accuracy of 92%.

Central to our approach was the integration of data augmentation techniques, crucial for enriching the diversity of the training dataset and enhancing the model's generalization capability. Through augmentation parameters encompassing rotation, shifts, shearing, zooming, and flips, we observed tangible improvements in accuracy and reduced loss across both training and validation datasets. Validation results further underscored the model's proficiency, with validation accuracy reaching an impressive 99.80% post-augmentation. Our findings not only demonstrate the effectiveness of tailored deep learning architectures and data

augmentation strategies but also highlight their potential for real-world application in breast cancer diagnosis. By surpassing the baseline accuracy and aligning with prior research emphasizing the significance of customized approaches, our study contributes to the ongoing efforts in medical image analysis.

Looking ahead, our work sets the stage for further exploration and refinement of deep learning methodologies in breast cancer detection. Future research endeavors may delve into advanced optimization techniques, such as transfer learning or ensemble methods, to unlock new avenues for improving diagnostic accuracy and patient outcomes. Ultimately, our study represents a crucial step forward in leveraging cutting-edge technology to address pressing healthcare challenges and underscores the transformative potential of deep learning in oncology.

VII .CONCLUSION

In conclusion, our study demonstrates the effectiveness of a modified AlexNet architecture and data augmentation techniques in improving breast cancer detection accuracy. By fine-tuning the model and enriching the training dataset, we achieved a significant accuracy improvement from 83% to 92%. These findings underscore the potential of deep learning in advancing diagnostic methodologies for breast cancer. Moving forward, further research efforts can focus on refining these techniques to enhance diagnostic accuracy and improve patient outcomes in clinical settings.

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