Breast Cancer:Tumor Detection in Mammogram Images Using Modified AlexNet Deep Convolution Neural Network.

A Report by:

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I. INTRODUCTION

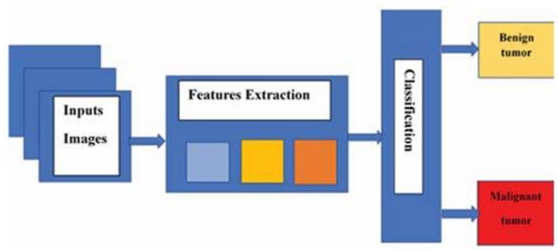
Breast cancer is one of the most common and dangerous types of cancer affecting women worldwide. Early detection is crucial for successful treatment, and one of the most effective ways to detect breast cancer is through mammogram images. Mammograms are X-ray images of the breast that can show tumors that may not be felt during a physical exam. However, analyzing these images to accurately identify whether a tumor is benign (non-cancerous) or malignant (cancerous) is a complex task. This is where technology, specifically deep learning and neural networks, can play a significant role.

In recent years, advancements in deep learning have made it possible to develop systems that can analyze medical images with a high degree of accuracy. One such system is the AlexNet Deep Convolutional Neural Network (DCNN). Originally designed for general image classification tasks, AlexNet has been adapted for various specific applications, including medical image analysis. In the study "Breast Cancer: Tumor Detection in Mammogram Images Using Modified AlexNet Deep Convolution Neural Network," researchers aimed to improve the accuracy of tumor detection in mammogram images by modifying the AlexNet architecture and using data augmentation techniques.

This report will explore the methodology and results of this study, provide a summary of the findings, offer a critical analysis, and conclude with the implications of this research and potential future directions. By understanding the significance of these technological advancements, we can appreciate how they contribute to improving breast cancer diagnosis and ultimately saving lives.

II. Short Summary

The study focused on improving the accuracy of detecting and classifying tumors in mammogram images, which are critical for diagnosing breast cancer. The researchers used the MIAS (Mammographic Image Analysis Society) database, a collection of mammogram images, to train and test their model. The primary goal was to modify the AlexNet DCNN, a well-known deep learning model, to effectively distinguish between benign and malignant tumors in these images.



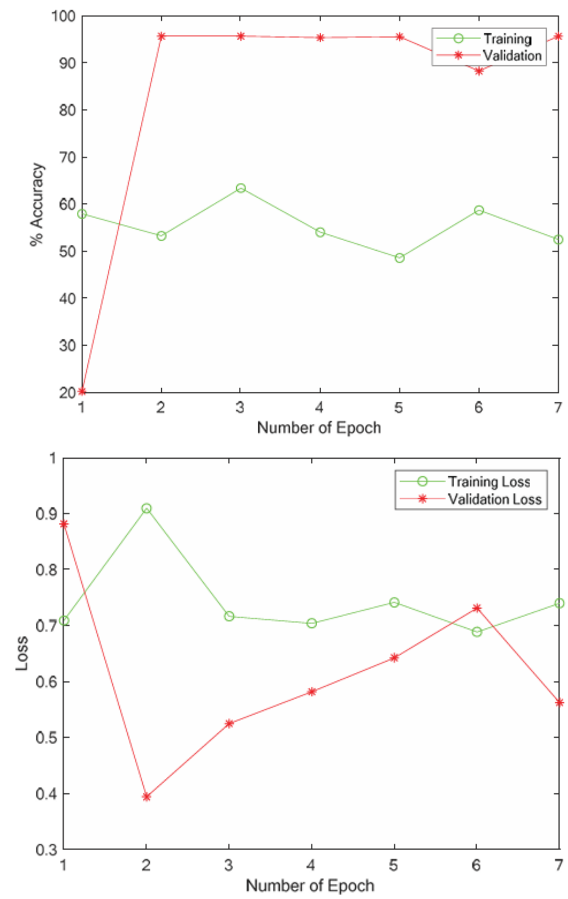
Project Block Diagram

To begin with, the images from the MIAS database were pre-processed to enhance their quality and remove noise using a Gaussian filter. This step was crucial because mammogram images often contain various levels of noise and contrast, which can make it difficult to identify tumors accurately. After pre-processing, the researchers applied data augmentation techniques to increase the size of their training dataset. Data augmentation involved downscaling the original images from 1024x1024 pixels to 64x64 pixels for faster processing. The images were then flipped horizontally and rotated at angles of 90, 180, and 270 degrees. This process resulted in a significant increase in the number of training samples, from 322 to 2,576 images.

Input image, grayscale (64 x 64)		
2	Conv1	96, 5 x 5 convolution with Stride =2 and zero padding
3	ReLu	Rectifier linear unit
4	Cross channel normalization	cross channel normalization with 5 channels per element
5	Max pooling layer	3x3 max pooling with stride [2 2] and zero padding
6	Conv2	256, 5 x 5 convolution filter, with Stride=1, and Padding = 2
7	ReLu	Same as previous
8	Cross channel normalization	Same as previous
9	Max pooling layer	Same as previous
10	Conv3	384, 3 x 3 convolution filter with Stride =1, and Padding = 1
11	ReLu	Same as previous
12	Conv4	Same as Conv3
13	ReLu	Same as previous
14	Conv5	256, 3 x 3 convolution filter with Stride=1, and Padding=1
15	ReLu	Same as previous
16	Max pooling layer	Same as previous
17	FC1	Fully connected layer with 4096 neurons
18	ReLu	Same as previous
19	Dropout	Dropout layer of 50%
20	FC2	Fully connected layer with 4096 neurons
21	ReLu	Same as previous
22	Dropout	Dropout layer of 50%
23	FC3	Fully connected layer of 2 neurons
24	Softmax	softmax
25	Classification layer	Output layer into two classes (Benign vs Malignant)

Architecture of the modified AlexNet

The AlexNet architecture was initially designed to classify images into 1000 different categories using the ImageNet dataset. However, for this study, the researchers modified the architecture to suit a two-class problem: benign and malignant tumors. They removed the last three layers of the standard AlexNet and replaced them with a fully connected layer, a softmax layer, and a classification layer. The convolutional layers were also adjusted to handle the specific requirements of mammogram image analysis.

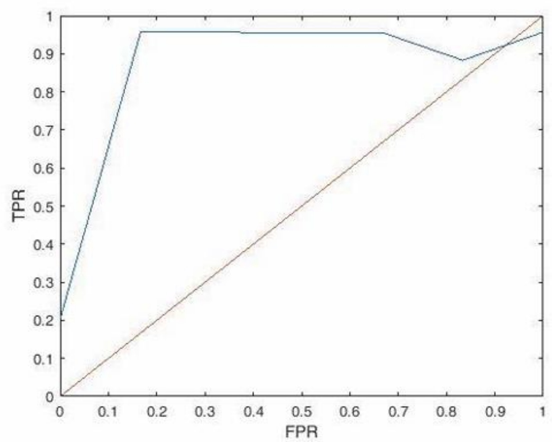


Percentage Accuracy(top) and loss function(bottom) for training and Validation

Training the modified AlexNet model involved using the stochastic gradient descent (SGDM) algorithm, with the dataset split into 31% for training and 69% for testing. Various parameters, such as learning rate and weight decay, were updated during the training process to minimize the loss function. The results were evaluated in two phases: without data augmentation and with data augmentation. The model demonstrated an overall accuracy of 95.70%, a significant improvement over traditional methods used in breast cancer diagnosis.

Actual / Classified as	Benign	Malignant
Benign	0.95	0.05
Malignant	0.054	0.946

Confusion Matrix of the system Model



ROC curve of the Evaluated model

III. Arguments/Critical Analysis

The study presents a compelling case for using a modified AlexNet DCNN to improve the accuracy of tumor detection in mammogram images. However, while the results are promising, several aspects warrant further discussion and critical analysis.

Firstly, the use of data augmentation is a notable strength of the study. By increasing the number of training samples through flipping and rotating the images, the researchers addressed one of the common challenges in deep learning: the need for large datasets. This approach not only enhanced the model's ability to generalize from the training data but also helped prevent overfitting, where the model performs well on training data but poorly on new, unseen data.

The choice to downscale the images from 1024x1024 pixels to 64x64 pixels was practical. This decision reduced the computational complexity and allowed the model to process the images more efficiently without compromising the quality of the results. It highlights the balance the researchers struck between computational efficiency and maintaining sufficient detail for accurate tumor detection.

However, there are limitations to this approach. While data augmentation increases the number of training samples, it does not introduce new information. The augmented images are simply transformed versions of the original images, meaning that the diversity of the dataset is still limited by the original 322 images. This could potentially limit the model's ability to generalize to real-world scenarios, where mammogram images may vary significantly in terms of quality and characteristics.

The modifications made to the AlexNet architecture were well-thought-out. By removing the last three layers and adding a fully connected layer, a softmax layer, and a classification layer, the researchers adapted the model to handle the specific task of distinguishing between benign and malignant tumors. The use of different convolutional filter sizes in the initial layers was also a strategic move, enabling the model to capture various features of the mammogram images more effectively.

Training the model using the stochastic gradient descent (SGDM) algorithm was a sound choice. This algorithm is known for its efficiency in training deep neural networks and has been widely used in various applications. The parameters such as learning rate and weight decay were carefully updated to minimize the loss function, which is essential for achieving high accuracy. Splitting the dataset into 31% for training and 69% for testing was a balanced approach, ensuring that the model had enough data to learn from while still being rigorously tested on a substantial portion of the dataset.

The study's results, showing an accuracy of 95.70%, are impressive and highlight the effectiveness of the modified AlexNet DCNN. The researchers demonstrated the impact of data augmentation by comparing the performance of the model with and without augmentation. The use of the ROC curve to summarize the performance and the calculation of the Area Under Curve (AUC) provided a clear and comprehensive evaluation of the model's accuracy.

While the study focuses on the accuracy metric, incorporating additional evaluation metrics such as precision, recall, and F1-score could provide a more rounded understanding of the model's performance. These metrics would help to assess how well the model balances the detection of true positives and the avoidance of false positives, offering deeper insights into its practical effectiveness.

Overall, the study presents a solid approach to enhancing breast cancer detection using deep learning. It showcases how modifications to existing neural network architectures and the application of data augmentation techniques can lead to significant improvements in accuracy. The findings suggest that with further refinement and exploration of additional evaluation metrics, this approach could be a valuable tool in medical imaging and cancer diagnosis.

IV. CONCLUSION

In conclusion, the study "Breast Cancer: Tumor Detection in Mammogram Images Using Modified AlexNet Deep Convolution Neural Network" illustrates the potential of deep learning in improving breast cancer diagnosis. By modifying the AlexNet architecture and employing data augmentation techniques, the researchers achieved an impressive accuracy of 95.70%. This marks a significant advancement over traditional methods used in mammogram analysis.

The use of the MIAS database, combined with pre-processing techniques and data augmentation, played a crucial role in enhancing the model's performance. The modifications to the AlexNet architecture, including the addition of a fully connected layer, a softmax layer, and a classification layer, were tailored to address the specific challenges of tumor classification in mammogram images. The training process, supported by the SGDM algorithm, further contributed to the model's effectiveness.

The study's results are promising, highlighting the importance of technological advancements in medical imaging. The approach of using deep learning models like AlexNet, with appropriate modifications and data augmentation, shows great potential in improving early detection and diagnosis of breast cancer. This can ultimately lead to better patient outcomes and more effective treatment strategies.

While the study primarily focused on accuracy, incorporating additional evaluation metrics such as precision, recall, and F1-score could provide a more comprehensive understanding of the model's performance. These metrics would offer deeper insights into how well the model detects true positives and avoids false positives, which is crucial for its practical application in medical settings.

In summary, this study underscores the significance of leveraging deep learning and neural networks to enhance breast cancer detection. As medical image analysis continues to evolve, further research and innovation will be essential in advancing our ability to diagnose and treat breast cancer effectively. The findings of this study pave the way for future developments in this field, offering hope for improved diagnostic tools and better healthcare outcomes.

V. REFERENCES

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