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A NOVEL CONVOLUTIONAL NEURAL NETWORK FOR BREAST CANCER DIAGNOSIS

Under the Guidance of
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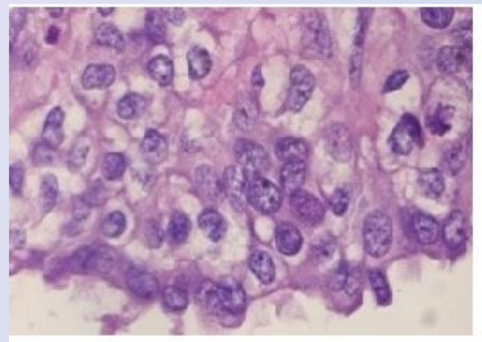
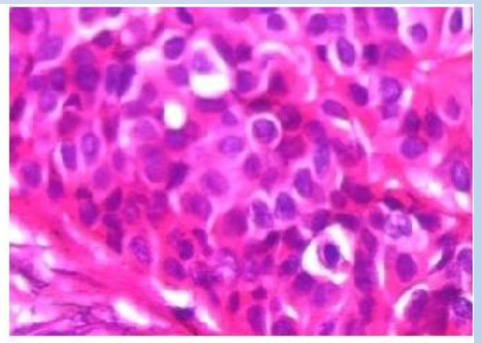
INTRODUCTION

Breast Cancer (BC) is the second leading causes of death across the world in women. Breast cancer is a malignant lesion formation in the breast region. Early detection of breast cancer helps in better selection of treatment and prevents risk on human life. Computer Aided Diagnosis system using Convolutional neural network (CNN) can detect early cancers and directs attention to unnoticeable findings in diagnostic images with increased efficiency and reduced cost.



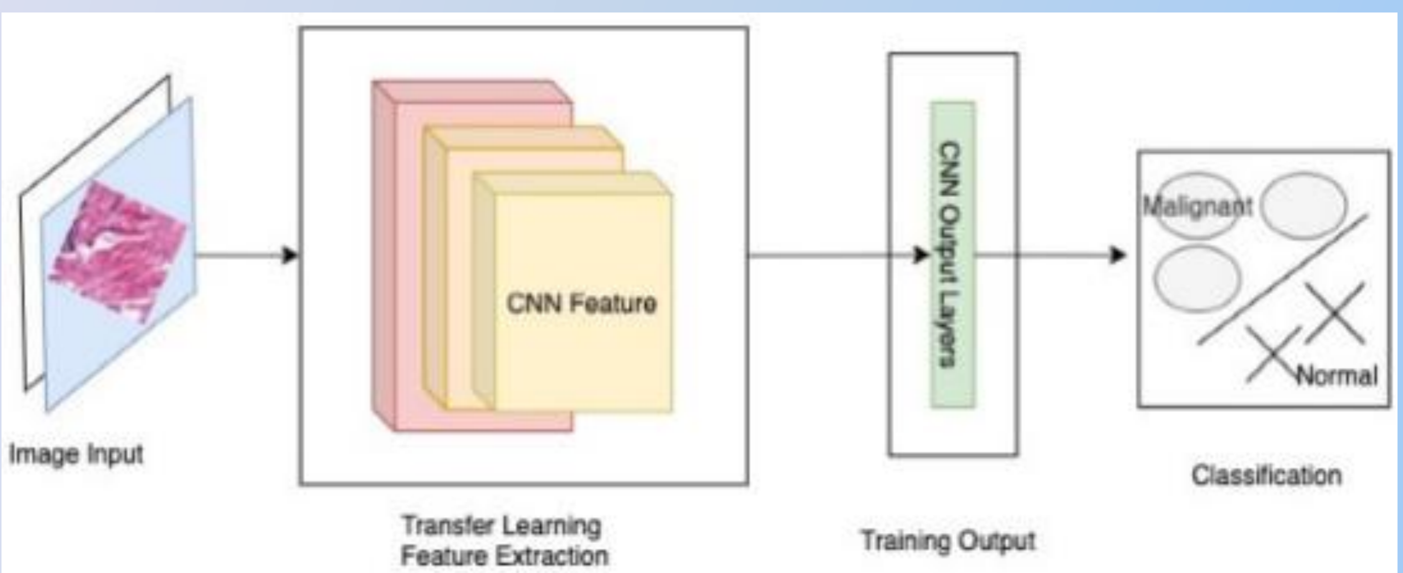
Benign Tumor



Malignant Tumor

EXISTING METHODOLOGY

Traditional CAD tools rely on manually extracted features, but the process can be tedious, difficult and non-generalizable. An alternative method for feature extraction is to learn features from whole images directly through a CNN. To train the CNN from scratch, however requires a large number of labelled images which are difficult to obtain. The solution is to reuse a pre-trained CNN model as a feature extractor with large image datasets from other fields.

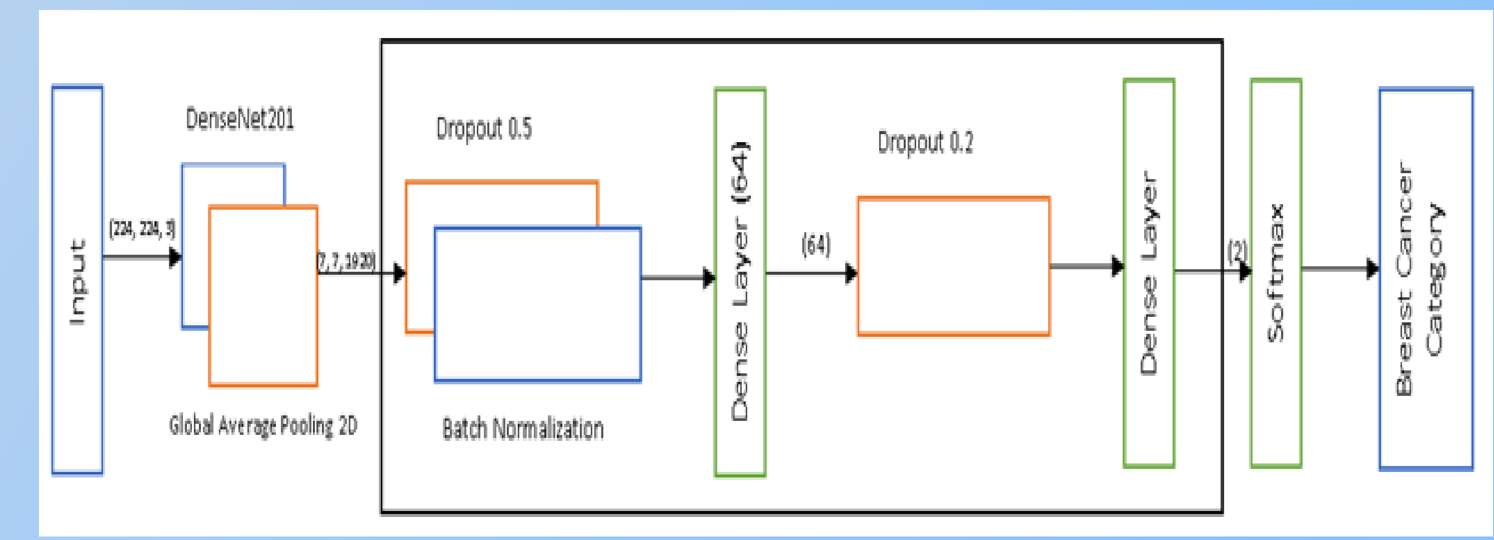


The disadvantages of connecting output layer to pre-trained CNN model directly is low performance and less accuracy compared to our proposed model.

DENSENET-201

This model consists of a total 201 deep CNN layers where each layer is arranged in such a way that it can solve over fitting issues while dealing with a small dataset. It also provides significant enhancements to the Imagenet database by solving the gradient descent problem. Compared to the AlexNet, GoogleNet and ResNet architectures, the DenseNet-201 pre-trained model will derive more complicated and essential features.

PROPOSED METHODOLOGY



PERFORMANCE METRICS

True Positives: The cases in which we predicted yes and the actual output is yes.
True Negatives: The cases in which we predicted yes but the actual output is no.
False Positives: The cases in which we predicted yes but the actual output is no.
False Negatives: The cases in which we predicted no and the actual output is no.

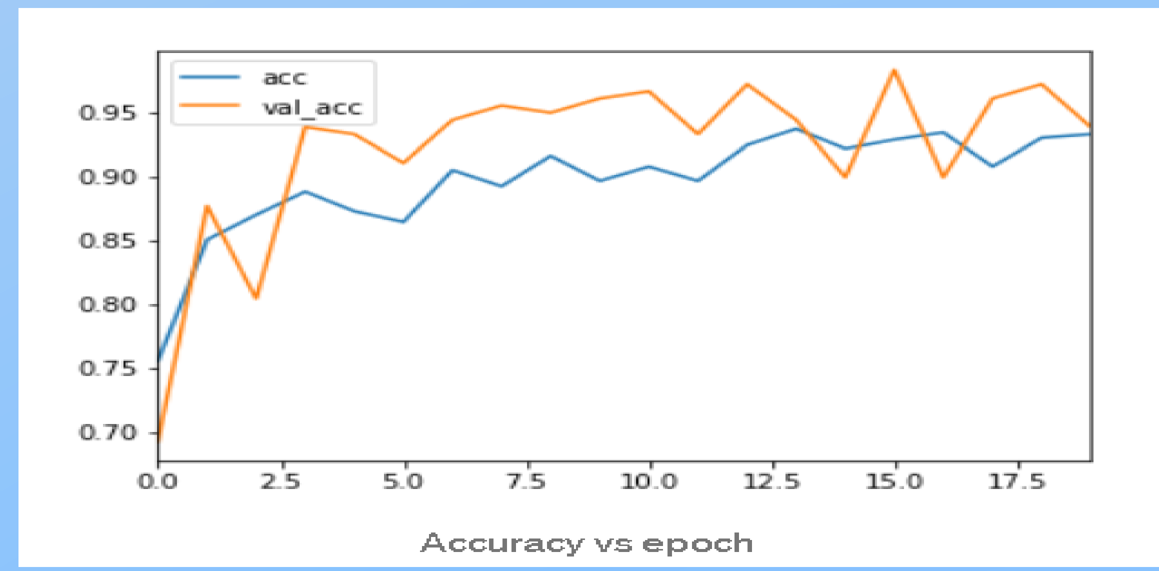
$$\textbf{Accuracy} = \frac{(True\ positive+True\ negitive)}{Number\ of\ samples} \times 100$$

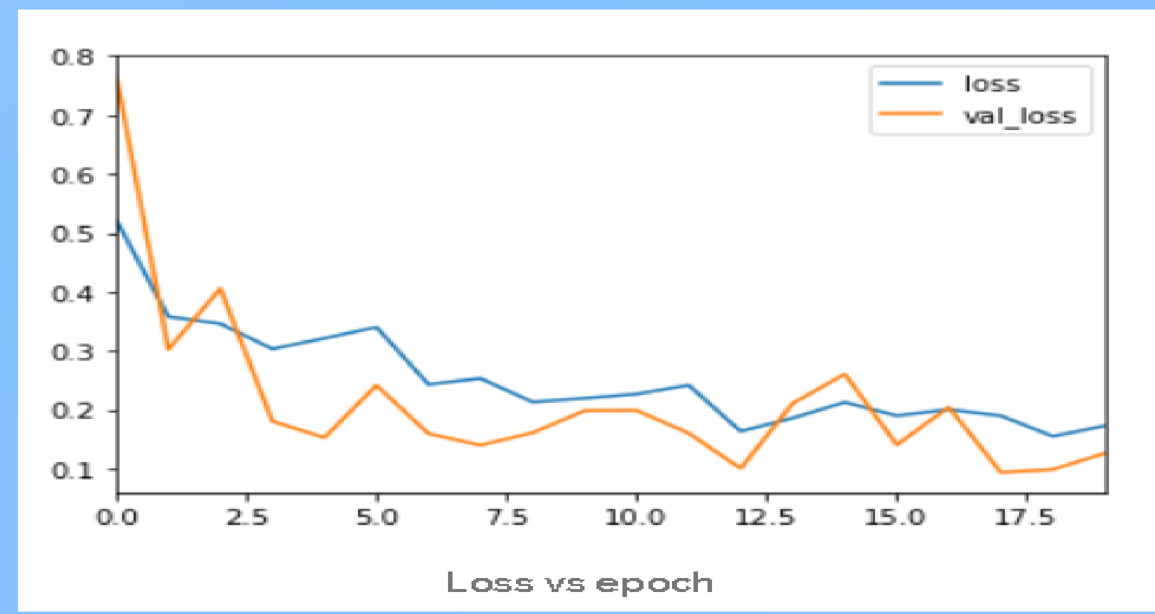
$$\textbf{Precision} = \frac{True\ positive}{(True\ positive+False\ negitive)}$$

$$\textbf{Recall} = \frac{True\ positive}{(True\ positive+False\ negitive)}$$

$$\textbf{F1-score} = \frac{2\times(Precision\times Recall)}{(Precision+Recall)}$$

RESULTS





Accuracy	Precision	Recall	F1-score	ROC-AUC
99.75%	0.93	0.97	0.95	0.88

Method	Dataset Used	Accuracy
SVM	Wisconsin	90.91%
Pre-trained VGG19 with multi-Layer Perception	BACH	92.71%
Xceptionand DenseNet CNNs	BreakHis	98.92%
Proposed Novel CNN with DenseNet-201	**BreakHis**	**99.75%**

CONCLUSION

The proposed CNN model using Transfer Learning with Modified DenseNet-201 gives better performance and high accuracy. This method can be used as an automated tool to assist doctors in breast cancer diagnosis and can increase the cancer survival rate.