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DIAGNOSIS OF BREAST CANCER THROUGH RESNET MODEL

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***Abstract*—**
BreastCancer[1],a type of Cancer, that is the most common cancer worldwide,although it also occur in men,albeit rarely.Breast Cancer can originate from different parts of the breast.Diagnosis of breast cancer involves a combination of imaging tests like mammogram,ultrasound,MRI and biopsy to examine tissue samples for the presence of cancer cells.About 1 in 40 women die due to this cancer.Early Diagnosis plays major role here.This research highlights majorly on mammographic[2] based analysis:Resnet-50.In addition to the model,an algorithm is pertained to model to diagnose the params. With this research,we target in making progress in early breast cancer detection using Resnet-50.

***Keywords*—** Breast Cancer, Mammographic Images, Bilateral Filter, ResNet.

I. INTRODUCTION

CNN-Image-related tasks including object detection, segmentation, and classification are good fits for Convolutional Neural Networks. They have been put to great use and have shown impressive results in a variety of computer vision tasks. Here are some key points about CNN s:

Pooling Layers: By reducing the spatial dimensions of the feature maps generated by convolutional layers, pooling layers help to lower computational complexity and increase the network's resilience to changes in input image quality.

Activation Functions: To provide non-linearity to the network and aid it learn complex patterns, non-linear activation functions as Rectified Linear Units are utilized after the convolutional layer.

Training with Back propagation: CNNs are trained using the backpropagation algorithm, which adjusts the network's weights to minimize the difference between ground truth labels and predicted outputs.

Pretrained Models: Pretrained CNN[3] models, have been trained on large datasets like ImageNet and are available for transfer learning. Transfer learning allows developers to use pretrained models as feature extractors or fine-tune them on specific datasets for tasks with limited data.For eg:ResNet.

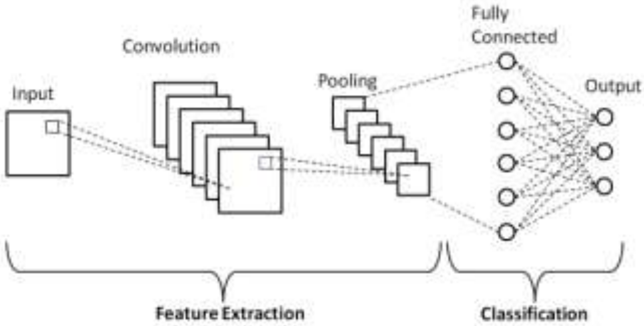
Applications: CNNs have been successfully applied to various tasks like VR(Virtual Reality),AR(Augmented Reality),Environmental Monitoring, etc.

Architecture Variants: Researchers continually propose new CNN architectures with improvements in performance, efficiency, and interpretability. Architectural variants like residual connections, skip connections, and attention mechanisms have been introduced to enhance CNNs' capabilities.

The architecture of a Convolutional Neural Network (CNN) typically consists of several layers arranged in a specific sequence. Here's an overview of the common layers and their arrangement in a typical CNN architecture layers:

1. **Input Layer**
2. **Convolutional Layer**

3. **Activation Layer**
4. **Pooling Layer**
5. **Fully-Connected Layer**
6. **Output Layer**



II.LITERATURE SURVEY

Breast Cancer is most common among women worldwide. There have been several studies conducted on this. Many models are there to predict this cancer.

Early detection of breast cancer through mammograms plays a key role in improving outcomes and reducing rates of mortality tied with this condition.

Here are some key points highlighting the importance of breast cancer early detection using mammograms:

Early Cancer Finding: Breast cancer can be noticed with mammograms, frequently even before visible symptoms appear. This allows for the diagnosis and treatment of the sickness at its most viable period.

Improved Treatment Options: When breast cancer is detected early, treatment options are typically more effective and less invasive. Early-stage cancers are often smaller and localized, making them more amenable to treatments such as surgery, radiation, and chemotherapy.

Reduced Mortality Rates: Studies have shown that regular mammogram screenings can significantly reduce mortality rates from breast cancer. Detecting the disease at an early stage increases the likelihood of successful treatment outcomes and survival.

Enhanced Survival Rates: Early detection through mammograms increases the chances of successful treatment and long-term survival. Women whose breast cancer is detected early have higher survival rates compared to those whose cancer is diagnosed at a later stage.

Potential for Less Aggressive Treatment: Early detection may allow for less aggressive treatment options, sparing patients from the side effects of intensive therapies and preserving quality of life.

Monitoring High-Risk Individuals: Mammograms are particularly important for women with an increased risk of breast cancer due to , genetic predisposition (e.g., BRCA gene mutations), or previous breast abnormalities. Regular screenings can help monitor these individuals closely and detect any changes early.

Cost-Effectiveness: Detecting breast cancer at an early stage through mammograms can be cost-effective compared to treating advanced-stage cancer. Early detection reduces the need for extensive treatments and associated healthcare costs.

Empowerment through Awareness: Regular mammogram screenings promote breast health awareness and encourage women to take an active role in their health by participating in preventive measures.

These are a few remarkable literature survey[5] for predicting breast cancer :

Lee and Kim et al.[1] mainly focuses on types of cancers and how they are formed.This paper helped us in identifying cancer to train model how to identify cancerous cells in mammographic images.The writers of this paper used 91 gene samples as dataset for identification.

Smith et al.[2]focuses mainly on higher stages of cancer.This model is trained to detect cancer of higher stages.EarlyDetection[4] is not efficiently done.Cancer detection in early stage is crucial step.

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Garcia et al.[3] highlights the comparisons between seven different neural networks predicting breast cancer.The most accurate result is considered.

Johnson et al.[4]mainly portrays the probability of cancer i.e. it predicts the percentage of cancer in mammographic images.But it's not the accurate the result.

III.PROPOSED SYSTEM

This model is proffered based on specific standards as follows:

- **Data Visualization**
- **Pre-Processing Techniques**
- **Model Creation and Evaluation**

Data Visualization

We have selected the datasets from internet .To make any prediction we definitely need the previous datasets. Existing data may help to get advances in the process very easily and fastly.

Pre-Processing Techniques

Pre-processing is a method that is applied to a dataset before it is visualized.It eliminated noise,null values and duplicates from the data set(if the data set is numerical).In image data set, applying pre processing techniques removes noise from images,sharpens edges,makes image more clear,etc..,There are many techniques to pre-process a dataset.For eg. Bilateral Filter,Gaussian Filter. The pre-processing technique used is bilateral filter.Because of it's efficiency,bilateral filter can be used for fast preprocessing of images and videos.It smoothens images,sharpens edges,and makes images clear.

Figure 1 is a comparison[6] between original and image after applying pre-processing.Images after pre-processing are more clear than original images.This helps a model to detect correctly.

Bilateral Filter: One method of nonlinear filtering is the bilateral filter[7]used in image processing and computer vision for smoothing images while preserving edges. Unlike linear filters such as Gaussian filters, which only consider the spatial neighborhood of each pixel, the bilateral filter also considers the variations in intensity between pixels close by. This property allows for able to be the bilateral filter to effectively wipe out noise from the image retaining significant edges and features intact.

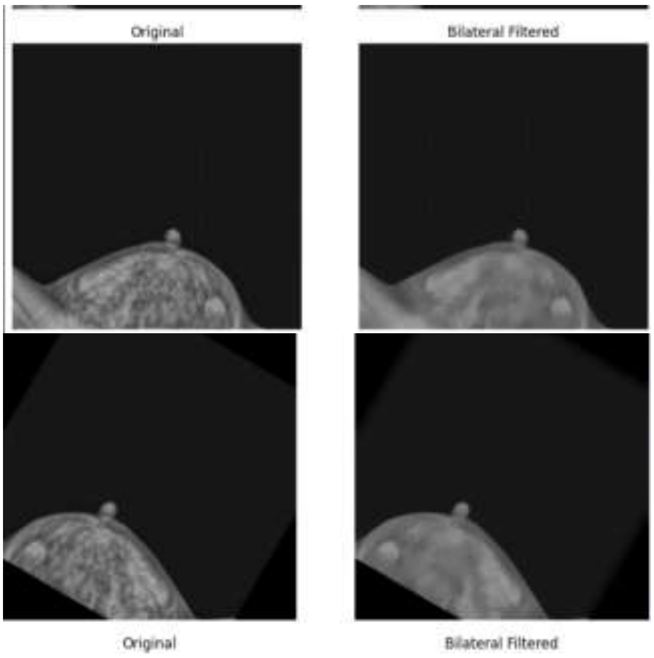

Fig1.**Images showing before and after preprocessing**

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Here's how the bilateral filter works:

Spatial Domain: Like other filters, the bilateral filter operates within a defined spatial neighborhood around each pixel. This neighborhood is typically specified by a window or kernel size.

Intensity Domain: The bilateral filter draws note of the intensity differences between pixels in addition to the physical neighborhood. It derives the weighted average of the intensities of the pixels within the spatial neighborhood by computing the difference in intensities between the center pixel and its neighbors along with the physical distance.

Weighting Function: The weighting function used in the bilateral filter consists of two components: an intensity kernel and a spatial kernel. Based on the spatial kernel, the weights are determined:spatial distance between pixels, while the intensity kernel considers the intensity differences.

Filtering Operation: For each pixel in the bilateral filter generates a weighted average of the intensities of the pixels in the spatial neighborhood of the picture where the weights are determined by the spatial and intensity kernels. This weighted average effectively smooths the image while preserving edges.

Parameters: The performance of the bilateral filter depends on the choice of parameters, including the spatial window size, the intensity standard deviation, and the spatial standard deviation. These parameters control The fit between edge preservation and noise reduction.

Applications of the bilateral filter include denoising of images corrupted by Gaussian or impulse noise, smoothing of depth maps in 3D reconstruction, and pre processing of images for edge-aware image processing tasks such as tone mapping and image fusion.

Fig.2 shows confusion matrix of the dataset taken.A confusion matrix is a table that defines the performance of a classification algorithm. Here, confusion matrix is drawn to define the performance of Resnet model.

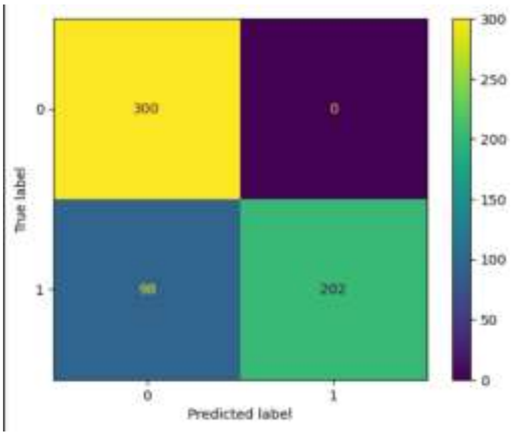

Fig 2.Confusion matrix of DDSM dataset

Model Creation and Evaluation

A model is a program for computers designed to identify patterns or draw conclusions from previously unknown datasets.A model is trained with some data for extracting some patterns or features.Data set is partitioned in train dataset and test dataset.

Define the Problem: Understand the problem you're trying to solve and determine if DL is the appropriate approach.

Data Collection and Preprocessing: Gather relevant data from your problem.This could involve gathering data from different resources cleaning it and preprocessing[8] it to preparing it suitable for training.

Choose Architecture: Select a suitable DL architecture for your problem, such such as Transformers for natural language processing, Recurrent Neural Networks for sequential data, and CNNs for tasks using shots.

Model Construction: Implement the chosen architecture using a DL framework like TensorFlow, PyTorch, or Keras. This involves defining the layers of the model, connecting them appropriately, and specifying any necessary parameters.
Training: Train the model on your data. This involves feeding the training boosting the model's parameters, evaluating the loss, and cycling data through the model using stochastic gradient descent (SGD) or Adam.

Validation: Validate the trained model using a separate validation data set to ensure it's not over fitting. Adjust hyper parameters if necessary based on validation performance.

```
loss: 0.4762 - recall: 0.8367
recall on the Test Set = 83.67 %
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Fig 3. Accuracy with ResNet-18.

Testing: Test the final trained model on a separate test data set to evaluate its performance. This data set should be unseen by the model during training and validation to provide an unbiased estimate of performance.

IV.CONCLUSION AND FUTURE SCOPE

Utilizing ResNet-50[9] architecture for breast cancer detection presents several significant advantages. ResNet-50, with its deep architecture comprising 50 layers, can effectively learn intricate features from mammogram images, enabling accurate classification of cancerous and non-cancerous tissues. The inclusion of residual connections helps mitigate the vanishing gradient problem, facilitating smoother and faster convergence during training. By leveraging large-scale datasets of annotated mammograms, ResNet-50 can be trained to achieve high sensitivity and specificity in detecting early signs of breast cancer, thereby potentially improving patient outcomes through timely diagnosis and treatment.

Enhanced Accuracy[10]: Further fine-tuning and optimization of ResNet-50 models for breast cancer detection can lead to even higher accuracy rates. Techniques such as transfer learning, data augmentation, and ensemble methods could be explored to enhance model performance.

Interpretability: Investigating methods to interpret the decisions made by ResNet-50 models can improve trust and understanding of the detection process. Techniques such as attention mechanisms and saliency maps can highlight regions of mammograms that contribute most to the classification decision, aiding radiologists in decision-making.
Multimodal Integration: Integrating additional modalities such as clinical data, genetic information, or other imaging techniques (e.g., MRI, ultrasound) with mammogram images could provide complementary information for more comprehensive and accurate breast cancer detection.

Real-time Deployment: Streamlining ResNet-50 models for real-time inference could enable their integration into clinical workflows, allowing for rapid analysis of mammograms and prompt feedback to healthcare professionals.

Personalized Medicine[11]: Tailoring ResNet-50 models to individual patient profiles and risk factors could facilitate personalized screening and treatment strategies, optimizing healthcare resources and outcomes.

Continual Learning: Implementing continual learning techniques would enable ResNet-50 models to adapt and improve over time as new data becomes available, ensuring their relevance and effectiveness in evolving clinical scenarios.

Table.1 shows accuracy of different models when compared to Resnet-50. It shows how better the performance of the model is.

Table 1. Accuracy of different models

Model	Accuracy
ResNet-50	50%
ResNet-18	80%
VGG-16	51%

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