BREAST CANCER DETECTION THROUGH MAMMOGRAPHIC IMAGE ANALYSIS

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ABSTRACT- Early recognition and treatment of breast tumors can lower death rates. As of right now, mammography is the most popular and reliable imaging method for diagnosing breast cancer. However, as it can be difficult and error-prone to identify malignant lumps from surrounding tissue, a misinterpretation of a mammography may lead to a false diagnosis rate. We propose constructing a model based on VGG16, as it exhibits the highest accuracy. To ensure optimal accuracy and assess the resilience of VGG16, an ablation research is conducted. To reduce artefacts and improve image quality, a variety of image processing methods are used with the right parameter values. The approach has taken the INbreast dataset which contains 7,632 images which belongs to 2 classes. The model VGG16 was built on the INbreast dataset for the breast cancer diagnosis. While working with a small number of complex medical images, our suggested approach which combines image processing, transfer learning, fine-tuning, and ablation study has shown a high accuracy rate in the classification of breast cancer. Through this research, we aim to contribute to the advancement of early breast cancer diagnosis by harnessing the adaptive and efficient characteristics of VGG16. The method has given the 96.47% accuracy for the mammogram INbreast dataset.

KEYWORDS: Mammogram, Breast Cancer, Image preprocessing, VGG16, Fine Tuning, INbreast Dataset.

I. INTRODUCTION

Breast cancer is a significant global health concern, affecting millions of women and causing substantial morbidity and mortality. Early detection plays a crucial role in improving treatment outcomes and reducing the overall impact of the disease. Mammography, a widely used imaging technique, has proven to be effective in detecting early signs of breast cancer. However, the accurate and timely interpretation of mammographic images poses a challenge, often requiring advanced computational methods for the improved diagnostic accuracy. Additionally, the VGG16 model is deployed to optimize the parameters and architecture of the deep learning models, thereby refining the breast cancer classification based on extracted features.

In recent years, deep learning models have gained traction in various fields for their ability to efficiently solve complex problems.

In order to provide timely patient services such as screening, diagnosis, and treatment, human resources and technology are crucial because time is a critical component in saving lives in the case of breast cancer. However, because of noise, distortions, and complicated structure in medical images, radiologists often find it difficult and time-consuming to diagnose tumours. This is made worse by the fact that there aren't enough physicians and radiologists in the globe, particularly in underdeveloped and rural nations, to interpret the screening results.

Furthermore, a rising patient volume increases the workload for radiologists, which frequently leads to incorrect cancer detection. Currently, the most widely utilised medical imaging modalities for the early diagnosis of malignant tumours in the breast are mammography, Magnetic Resonance Imaging (MRI), and ultrasound. Among other modalities, mammography-based diagnosis performs better in this regard than symptoms-based diagnosis. With a broad dynamic range and minimal noise, digital mammography yields images of excellent quality at a comparatively low radiation dosage.

The incidence of breast cancer ranks second only to lung cancer, making it a significant health concern worldwide. This disease has seen a progressive increase in occurrence across both economically developing and developed nations[1]. Regrettably, 15% of breast cancer-related deaths stem from a lack of early detection, highlighting the critical importance of timely diagnosis[2].

The precise etiology of breast cancer remains elusive, contributing to challenges in its early detection. The dense and heterogeneous structure of women's breasts further complicates the identification process. Nonetheless, early detection significantly improves the prognosis and survival rates for affected individuals.

Enhancing survival rates hinges upon the development and implementation of efficient diagnostic methodologies capable of timely breast cancer detection[3]. These methodologies play a pivotal role in extending the lifespan of affected individuals and improving overall outcomes.
Various imaging modalities are employed for breast imaging to facilitate early identification and diagnosis of potential abnormalities. Among all these modalities, ultrasound imaging stands out as a popular choice due to its utilization of acoustic waves, which eliminates the risk of ionizing radiation exposure. However, while ultrasound imaging offers advantages in safety, it may not provide the detailed information, particularly about regarding microcalcifications[4].
Microcalcifications play a crucial role in the early detection of breast cancer, as they serve as subtle indicators of abnormal cellular activity. These minute deposits of calcium are often imperceptible through symptoms but are readily detectable through the imaging modalities. Unfortunately, ultrasound imaging may not offer the level of details required to effectively identify the microcalcifications[4].
Therefore, despite its safety profile, ultrasound imaging may not be the optimal choice for capturing detailed information about microcalcifications in breast tissue. As such, complementary imaging modalities or additional diagnostic approaches may be necessary to ensure comprehensive evaluation and timely detection of breast cancer.
Mammography stands out as a specialized and non-invasive imaging modality designed specifically for breast imaging. It utilizes low-dose X-ray radiation to detect microcalcifications within the breast tissue. One of its primary advantages is the ability to identify cancerous abnormalities even before physical symptoms manifest in patients. Digital mammography in particular, significantly influences the potential for early detection of breast cancer.
However, the manual interpretation of mammogram images poses significant challenges for radiologists, often resulting in errors for the diagnosis. Detecting microcalcifications and categorizing their severity manually is a laborious and error-prone process. Leveraging Computer-Aided Diagnosis (CAD) systems to automatically detect microcalcifications and categorize their severity can substantially improve the diagnostic accuracy.
CAD systems integrate both the knowledge and experience of experts, along with advanced design principles, to enhance the classification accuracy of mammogram images. The severity of microcalcifications serves as a crucial indicator of the nature of abnormalities within the breast tissue, distinguishing between benign and malignant types of the severity[5].
Benign microcalcifications typically indicate non-cancerous conditions, where benign tumors do not invade neighboring tissues. In contrast, to the malignant microcalcifications suggest cancerous abnormalities, as malignant tumors tend to invade aggressively and have the potential to spread to surrounding breast tissues.
Therefore, the ability to detect and differentiate between various severities of microcalcifications is essential for early diagnosis and effective management of breast cancer. Integrating CAD systems into mammography workflows can significantly enhance the early detection and classification of breast abnormalities, ultimately improving patient outcomes.
The integration of CAD systems into mammography workflows holds great potential for improving the early detection and diagnosis of breast cancer by accurately identifying and classifying microcalcifications based on their severity.

Fig.1: Steps involved in Model

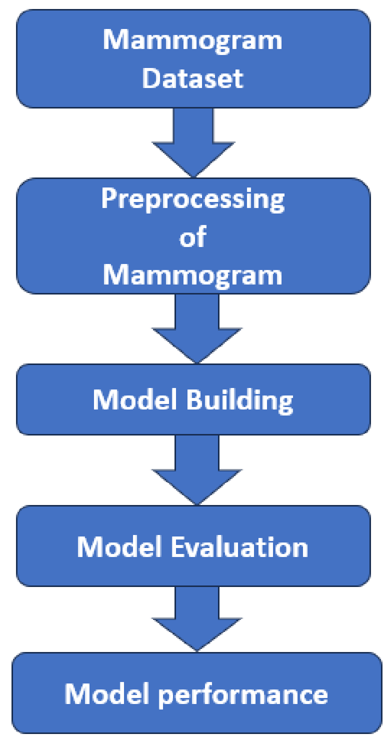

Fig. 1 Illustrates the proposed workflow for the problems of the detection and classification pf the breast cancer using digital mammographic images. After pre-processing the Region of Interest(ROI) have been extracted, than the features are extracted using VGG16 deep-learning architecture, and then these features are analyzed. For feature analysis was carried out for ensuring the type of classifier for the problem. Than the Flamingo Search optimization algorithm is implemented for the detection and the classification of the microcalcification in the digital mammogram images.
The prime goal of this proposed work is to detect the breast cancer and then classifying the severity of breast cancer benign or malignant effectively.

Several research studies [6-9] have been proposed recently for design of deep learning based mammographic image classification frameworks, but this work intends to utilize the deep learning based extraction of the features and this aims to improve the diagnosis of the breast cancer through the deep learning architecture which is the Computational Neural Network model VGG16 for the tumor detection in the mammogram image input i.e., benign tumor or malignant tumor.

Breast cancer is a major cause of illness and death worldwide, which emphasises the critical need for cutting-edge diagnostic methods to promote early identification and improve efficacy of treatment. There is a lot of potential here for using deep learning algorithms in medical imaging, especially for mammography analysis. This research main goal is to analyse mammography images using convolutional neural networks, namely the VGG16 architecture, and spot tiny patterns that could be signs of breast cancer[10].

The practical use of deep learning methods, in particular CNN architecture like VGG16, represents a major breakthrough in the accuracy of medical imaging and diagnosis. Researchers and medical practitioners may be able to improve the identification of minute abnormalities in mammography pictures by utilising the power of these algorithms, which could ultimately result in earlier diagnosis and more successful treatment plans. Deep learning architectures, such as VGG16, have the potential to transform breast cancer detection because of their capacity to adapt to the particular qualities of mammograms.

The capacity of deep learning models like VGG16 to extract minute details from complicated images is one of the main benefits of using them in mammography analysis. Mammograms frequently show minute patterns and anomalies that are difficult for humans to interpret but that are detectable by advanced algorithms. VGG16 can detect these subtle cues through intensive training on big datasets, improving healthcare professionals' diagnostic abilities and possibly lowering the rate of false positives and false negatives in breast cancer screening.

Furthermore, the potential for reducing the inherent subjectivity associated with human interpretation exists in the incorporation of deep learning algorithms into mammography analysis. Variations in radiologists' degrees of training and experience can cause discrepancies in the precision of their diagnoses. Deep learning models, such as VGG16, on the other hand, provide a standardised method of picture analysis, delivering objective and consistent evaluations across various datasets and clinical contexts. In the end, this standardised method improves patient outcomes and lowers healthcare inequities by enhancing the consistency and reliability of breast cancer diagnosis. As the tumor need to be diagnosed early to increase survival rate.

One benefit of deep learning models like VGG16 is their tremendous scalability, which enables ongoing improvement and optimisation. In order to improve the effectiveness and accuracy of these models in mammography analysis, they can be updated and adjusted in response to new data and technical developments. Deep learning-based methods can continue to lead the way in breast cancer diagnosis thanks to this iterative process of improvement, which also helps them adapt to changing clinical requirements and become more practical in everyday settings.

Deep learning models like VGG16 have the potential to enable personalised therapy in the treatment of breast cancer in addition to their diagnostic capabilities. Through analysis these models can help doctors customise treatment strategies for specific patients by considering variables including tumour subtype, molecular features, and treatment response. They do this by using enormous volumes of patient data, including genetic profiles, clinical histories, and mammography pictures. This customised strategy to managing breast cancer may maximise treatment results and raise the standard of care provided to patients everywhere.

II. LITERATURE SURVEY

Early diagnosis of Breast cancer through mammographic image analysis is a popular research topic in Medical analytics.There have been several studies conducted on this topic using various Optimization and Deep learning techniques. Here are some of the notable literature survey for Breast cancer Detection:

Anna Horvath et.al [11]: Explains how Artificial Intelligence(AI) may be used to screen for breast cancer. It calls into question the usefulness of AI technologies in this field in comparison to their hype. Absence of extensive validation: The generalizability of some studies findings may be hampered by small datasets or insufficient validation. It’s reliance on a limited dataset, potentially hindering the generalizability of the deep learning model's performance to broader populations or scenarios.

Gubern Merida et.al [12]: The methodology employs VGG16 architecture, tailored for mammography analysis, to detect breast cancer indicators. Data preprocessing and finetuning techniques optimize model performance. Rigorous validation, utilizing diverse datasets and performance metrics, assesses model effectiveness. Future enhancements may include advanced data augmentation, transfer learning, ensemble methods, and integration.

Mobarak Zourhri et.al in 2023[13]: This Study uses the Transfer Learning that improves the precision for classifying breast tumor using ultra sound images. The public Dataset with 9016 ultrasound images have been used for classification. In these the model usage of VGG19 have given the accurate results for the classifying the benign and malignant tumor.

Kampharia et.al in 2023[14]: It was found that a pre-trained model provides a better performance on a DDSM dataset and is able to minimize the loss function during the gradient descent process. This was implemented using various image classification models (AlexNet, VGG16, VGG19, MVGG, Mobile Net, and ResNet50) which were modified by tuning the feed-forward neural networks. The proposed hybrid model, a combination of MVGG and ImageNet, performed best and provided an accuracy of 94.3%, a precision of 93.5%, a sensitivity of 93.7% and an F1-score of 93.7%. Two experiments were conducted, to classify cancerous and non-cancerous mammography lesions.

Sannasi Chakravarthy et.al in 2022[15]: This Study integrated the concept of Deep Learning with Extreme Learning Machine (ELM) that is optimized with the crow search algorithm. This study utilizes the ResNet18 based deep features extracted with ICS-ELM algorithm. This study worked on different Datasets like DDSM, MIAS, INbreast for the better classification of tumor in mammograms.

Qi et.al in 2021[16]: Worked on algorithms and infrared images and transformed edges into curves to produce intersections of breast cancer detection. This model might be utilized in healthcare facilities that have ultrasonic equipment. Sonographers and breast surgeons could utilize this model to make an immediate diagnosis after the ultrasound evaluation.

Song et.al in 2020[17]: In this survey they have used the Fully Convolutional Networks to detect and segment the corners of aerial images. Their work have achieved the good performance by outperforming several algorithms and their comparisons.

These studies demonstrate the wide range of techniques and approaches used in detecting the tumor in mammograms. They also highlight the importance of preprocessing, Region Extraction, Feature extraction and classification for later analysis.

III. PROPOSED SYSTEM

One popular existing deep learning method for the classification of breast tumor is Convolutional Neural Network(CNNs). The CNNs are particularly well-suited for image classification tasks because they can automatically learn relevant features from the images themselves. In the context of mammogram classification, CNNs can be trained on labeled datasets of mammogram images with the corresponding tumor classifications (e.g., malignant, benign). The CNN learns to extract patterns and features from the images that are indicative of tumor presence or absence, enabling accurate classification. This method is well suited for the mammogram datasets like DDSM, MIAS and INbreast[18].

Our Proposed Model particularly uses the optimization algorithm that which used to find the optimal features which can accurately classify the tumor in mammogram. This model provide the optimal results for the early diagnosis of breast cancer.

Our Model contains the following steps:

~ Mammogram Dataset Analysis
~ Pre-processing of mammogram
~ Model Building
~ Model Evaluation
~ Model performance

A. Mammogram Dataset Analysis

The Proposed model was evaluated using the digital mammogram images as input downloaded from the CBIS-Digital Database for Screening Mammography (DDSM), Mammographic Image Analysis Society (MIAS), and INbreast database.

The MIAS dataset possess the measurements of about 160 distinct patients data with the quantity of 322 mammogram images abstracted from both right and left-side breasts. These digital images of mammograms available with a size of 1024 X 1024 pixel data. The mammograms in MIAS dataset obtained at MLO view with three different classes: fatty, dense, fatty glandular, and dense. Herein the dataset consists of Abnormal mammogram images which is divided into benign severity and malignant. The dataset can be accessible publicly at peipa archive[19].

The mammograms in INbreast dataset were obtained from the Center of Breast University Hospital, Portugal. But the INbreast dataset is less used comparative to MIAS dataset in the medical community, it has a advantage that its data are Full-Field Digital Mammogram(FFDM)[20]. The INbreast dataset consists of 7,632 mammograms those belongs to the 2 different classes one is of benign mass and the other is of malignant mass. The dataset can be downloaded from the data.madeley.com website provides the INbreast mammogram images.

B. Pre-processing of Mammogram

The captured images uses the mammography technique using lower X-ray radiation, obtained together with the markers and pectoral muscles. The effectiveness of the Computer Aided Diagnosis system is enhanced by suppressing the noise using filtering methods[21]. The mammogram images in any dataset contains impulse noise, which may included during its Procurement.

The paper uses Bilateral filter to get rid of the impulse Noise. The bilateral filter is a non-linear filter used for edge-preserving smoothing and noise reduction in images. It differs from conventional linear filters e.g., Gaussian filter in that it considers both the spatial distance and the intensity difference when performing smoothing. This makes it particularly effective in preserving edges while reducing noise[22].

By applying Bilateral Filter the following objectives can be obtained they are as follows:

- Noise Reduction
- Edge Preservation
- Enhancement of subtle structures

Noise Reduction: Mammograms may contain noise due to various factors such as equipment limitations and radiation. The bilateral filter helps reduce noise while retaining the details necessary for diagnosis.

Edge Preservation: Mammograms contain important edges and structures indicative of abnormalities or lesions. Preserving these edges is critical for radiologists to accurately identify and analyze potential areas of concern. The bilateral filter's edge-preserving property ensures that important edges are retained while smoothing out noise.

Enhancement of subtle structures: Mammograms often contain subtle structures that may not be immediately visible due to noise or low contrast. By reducing noise and enhancing contrast, the bilateral filter can help make these structures more discernible, aiding in early detection and diagnosis.

The bilateral function takes several parameters, including the diameter of the pixel neighborhood, sigma values in color space, and sigma values in coordinate space, allowing for fine-tuning based on the specific characteristics of the image. By adjusting these parameters and applying the bilateral filter to mammograms, we can obtain clearer, more visually informative images that facilitate accurate interpretation and diagnosis. The bilateral filter is applied on the every image in mammogram dataset to enhance the picture quality and remove the noise in each mammogram and produces the smoothed image for the further process. The smoothed mammogram clearly possess the tumor region in the mammogram and that image can be trained and tested by the model without any artifacts. The Fig.2. describes how the bilateral filter worked for generating and Enhanced mammogram from the original mammogram.

Original Mammogram

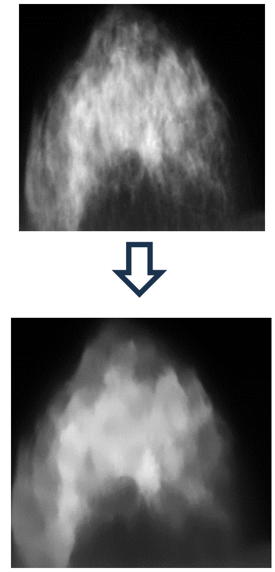

Fig. 2. Enhanced Mammogram

The Fig. 2. Describes the working of the bilateral filter on the original mammogram input and removes the noise from the mammogram and provides an enhanced mammogram which is used for the further classification[23].

Region Of Interest (ROI) Extraction:

ROI typically refers to a specific area or region within a mammogram image that is of particular interest for further analysis or examination. The ROI identifies the tumor part in the mammogram from the preprocessed mammogram.

The ROI specifies the range of tumor that had been spread in the breast. This gives the clear vision to the model for the further diagnosis[24].

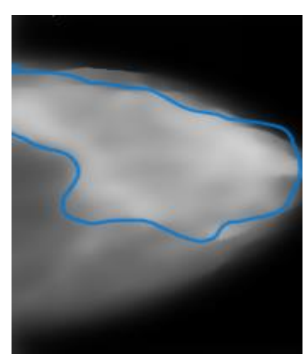

Fig.3. ROI Extraction in Mammogram

The Fig.3. specifies the tumor region in mammogram which focus the attention on specific areas that may require further investigation. In CAD systems, identifying regions of interest is a crucial step in automating the detection and analysis of abnormalities in mammogram images.

C. Model Building

Feature extraction is to extract the information as the compactable features from the mammogram input. In recent times the deep learning techniques has been widely employed for solving the several applications such as security and defense, industrial research and medical systems. Feature Extraction is the easier and fastest way to use the representational capability of the pre-trained deep networks. Convolutional Neural Network is very hot topic in applications of both the machine learning and artificial intelligence.

A highly effective common methodology to learn deeply on smaller image datasets is to leverage a pretrained model. A pretrained network is a saved network that was trained previously on the larger dataset, typically a huge image classification. If this trained dataset is general and large enough the spatial feature hierarchy learned using the pretrained model can act as an effective network for visual world. So, its features proven to be used for several classification problems, if these new tasks presents the different output classes when differentiated with the original one. For example, we might train a network model on ImageNet database were output classes are objects and animals and reutilize this trained model for other task as remote in identifying lesions of mammogram inputs. Such adaptability and portability of the learned feature vectors implements distinct tasks is advantage of deep learning as compared with other shallow learning methodologies, and that makes a deep learning very efficient one for the smaller data problems.

The VGG16 pretrained network train on color images and to make that work on gray-scale mammogram the mammogram image inputs are converted to RGB, this work makes that happen by making the gray-scale mammogram to repeat image array three times on newer dimension. The way it works that by creating the newer dimension for placing the channels and it will repeat the existing array for three times on this newer dimension. That will make the same image overall the three channels so the performance of model be the same as it was on the RGB image.

The Convolutional Neural Network being the popular for both feature extraction and learning methods. The concept of this extraction of features from the mammogram inputs works by employing the pretrained network by making use of layer activations as features. Therefore these activations as features are applied to train a model. Furthermore DarkNet19, ResNet18, AlexNet and VGG16[25] architectures being used popularly for recent studies for feature extraction. Among all the CNNs, the Visual Geometry Group16(VGG16) is the CNN, which was widely used in the applications of the image processing and signal. VGG has many variants: VGG11, VGG13, VGG16, VGG19. For the simple and higher compact representation of VGG16 makes it popular for feature extraction. As the naming concern, VGG16 is the Convolutional Neural Network with 16 deep-layers and so termed as VGG16[26].

The VGG16 architecture require image inputs of size 224-by-224 , but mammograms in employed dataset have different sizes. The automatic resizing of the testing and training dataset images are done before applied to the network to overcome the size. The VGG16 model that generates hierarchical representation of applied input mammogram images, where the deeper layers hold the high level feature vectors of the earlier layers. To obtain the input mammograms feature representation, global activation pooling layer(fc2) is employed to the end of the architecture model. Thus the network to pools feature representation, all spatial locations, provides a total of 512 features. Thus the VGG16 network is employed for the feature extraction, final classification layer was not used. Even though mammograms differ from the mammogram images available in ImageNet database, the VGG16 model utilized for extracting and training the efficient feature vectors related to each of applied mammogram input images.

Max-pooling layers extract significant attributes while minimising spatial dimensions using a 2x2 pooling window. Dropout layers are employed to prevent overfitting by randomly deactivating neurons during training. The convolutional layers are followed by the 2D feature maps being flattened into a vector. two closely linked.There are 256 neurons in these layers with a 0.5 dropout rateand ReLU activation. Ultimately, it is simpler to categorise data into two groups, such as Real and Fake, thanks to the output layer's softmax activation function.

As The VGG16 architecture has been shown in Fig.4.

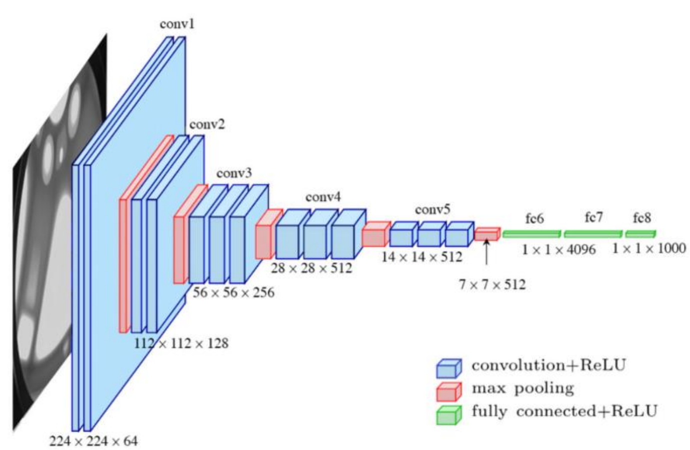

Fig.4: VGG16 Model Architecture

Train-Test and Val Data Splitting:

The training and testing subsets of the dataset are separated according to a predetermined ratio. Through random sampling, the script ensures a balanced distribution and copies images to respective train and test directories.

```
Total for trainning :  Found 7632 files belonging to 2 classes
['Benign Masses', 'Malignant Masses']

For Training :  Found 7632 images belonging to 2 classes.

For Val :  Found 7427 images belonging to 2 classes.

For Test :  Found 7427 images belonging to 2 classes.
```

Fig.5: Train-Test Data

The Fig.5 depicts that the total no.of mammogram images that are divided into two classes benign and malignant. Both the training and testing data consists of the total mammogram images of 7,632 in INbreast dataset.

Model Training:

The VGG16 architecture require image inputs of size 224-by-224 , but mammograms in employed dataset have different sizes. The automatic resizing of the testing and training dataset images are done before applied to the network to overcome the size. The VGG16 model that generates hierarchical representation of applied input mammogram images, where the deeper layers hold the high level feature vectors of the earlier layers. To obtain the input mammograms feature representation, global activation pooling layer(fc2) is employed to the end of the architecture model. Thus the network to pools feature representation, all spatial locations, provides a total of 512 features.

Thus the VGG16 network is employed for the feature extraction, final classification layer was not used. Even though mammograms differ from the mammogram images available in ImageNet database, the VGG16 model utilized for extracting and training the efficient feature vectors related to each of applied mammogram input images.

Utilizing 3x3 filters and ReLU activation, it employs max-pooling for feature extraction. Despite its popularity, its larger model size affects deployment efficiency[24].

The mammogram Inbreast dataset has a parameters after Training the model is as follows:

```
...
Total params: 134,268,738
Trainable params: 121,913,858
Non-trainable params: 12,354,880
```

Fig.6: Model Summary

D. Model Evaluation

Post-training, both the CNN and VGG16 models are evaluated on the testing dataset. Essential metrics like accuracy and loss are computed to gauge their tumor detection performance. A comparative analysis between the models helps discern their respective strengths and weaknesses, guiding further optimization endeavors.

Evaluation Metrics:

The evaluation of the proposed model involves assessing its performance using various metrics, as outlined. These metrics provide insights into different aspects of classification effectiveness.

Accuracy: The model overall performance by the ratio of correctly classified instances.

Recall: The tampered images percentage that are classified accurately out of total images.

Precision: This quantifies the images proportion as forged.

F1 Score: It is a combined measure of the recall and precision that indicates the overall accuracy of the test.

The model has been evaluated with the performance of other model like VGG19 and ResNet50.

VGG19 is also a CNN architecture. It belongs to the VGG model family and is renowned for being straightforward and efficient. Specifically, VGG19 has 19 layers total—3 fully connected layers and 16 convolutional layers. Max-pooling layers are included between the deeply stacked 3x3 convolutional layers in the design to facilitate down sampling. The non-linearity of VGG19 is brought forth by its uniform architecture, which contains a ReLU activation function after every convolutional layer. Classifiers are the completely connected layers at the conclusion of the network[27].

ResNet50 network works on the principle taking the deep CNN and adding the shortcut to skip the few convolution layers at a time. This shortcut connections create the residual blocks. The convolution layer output was added to the residual block. The deep residual learning framework was designed to address the degradation issue caused by the network deeper. The architecture is of the 34 layer network in which skip connection or the residual blocks are added resulting to residual network[28].

IV. RESULT AND ANALYSIS

Analyzing each model's loss curve, training and validation accuracy is part of the evaluation process. The percentage of accurately categorized samples using a different validation dataset that was not utilized for training is known as validation accuracy, while the training accuracy curve shows the model's learning progress. A drop in validation accuracy relative to training could be a sign of overfitting. The model's capacity to reduce loss during training is demonstrated by the training loss curve. A spike in comparison to training loss implies overfitting; the validation loss curve shows performance on independent testing data. Dataset is divided in an 80:20 ratio for the experiment. Validation set adjusts hyperparameters, guards against overfitting, and assesses the model's performance[29]. Training is stopped when validation error is minimized through validation performance monitoring, which enhances generalization. Exceptional accuracy of 96.47% is achieved by VGG16 shown in Fig. 4 which depicts the training and validation loss and recall on the train and val dataset of mammogram INbreast with the maximum epochs of 15 on the x-axis and y-axis contains the recall and loss.

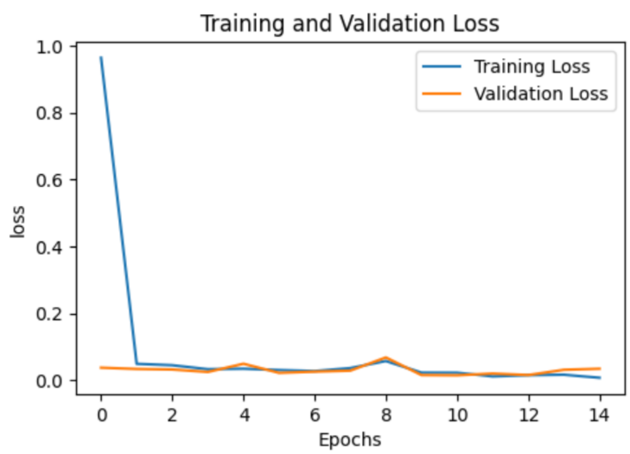

Fig.7: VGG16 model

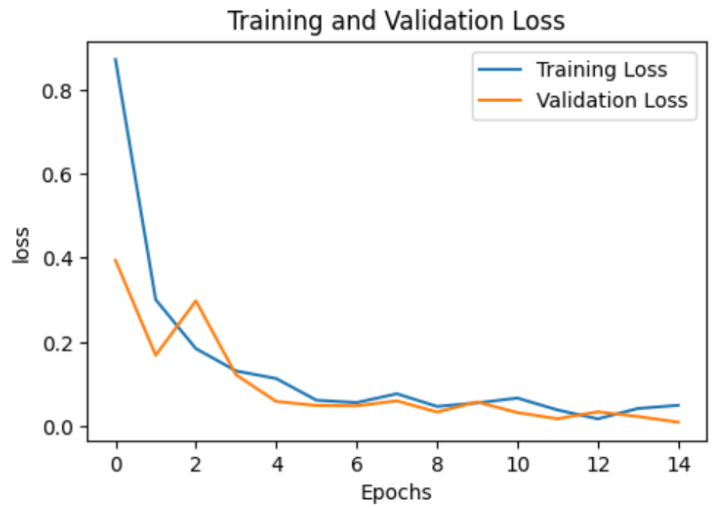

Fig.8: VGG19 model

The model's performance on testing data that was not used in the training phase is shown by the validation accuracy curve. A decrease in the validation accuracy curve relative to the training accuracy curve indicates that the model is overfitting the training set, which makes it difficult for it to generalise to new data. Comparably, the model's ability to minimise the training loss function over time is shown by the training loss curve. The curve usually falls as training goes on because the model gets better at fitting the training set. As an illustration of how successfully the model minimises the loss function on independent testing data that it has not experienced during training, the validation loss curve shows contrast. When the validation loss curve begins to rise compared to the training loss curve, it signifies overfitting, prompting the need to halt the training process promptly.

Confusion matrix: An effective method for assessing a classification model's effectiveness is a confusion matrix. In a confusion matrix, the actual labels of the data are represented by one axis, and the predicted labels are represented by the other. It facilitates comprehension of the model's performance in relation to various classes. Each column of the matrix of uncertainty represents an instance in a predicted class, while each row represents an instance in an actual class, when using VGG16 or any other image classification model. The examples that are correctly classified are represented by the diagonal members of the confusion matrix, and the misclassifications are represented by the off-diagonal elements.

It displays the proportion of accurate and inaccurate predictions the model produced in relation to the data's actual results.

- True Positive (TP): The classifier correctly predicted the positive class, represented as 1,1 in the matrix.

- False Positive (FP): Type I error, or 0,1 in the matrix, indicates that the classifier predicted the positive class wrongly.
- True Negative (TN): The classifier predicted the negative class—shown in the matrix as 0,0—correctly.
- False Negative (FN): A Type II mistake occurred when the classifier predicted the negative class erroneously, which is shown in the matrix as 1,0.

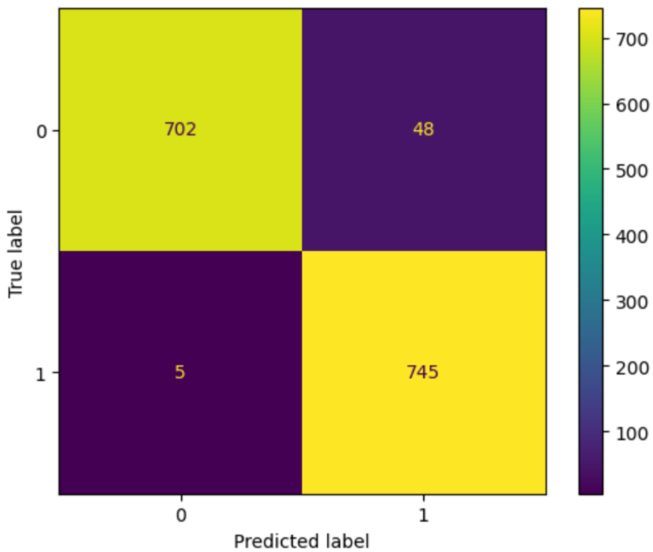

Fig.9: Confusion matrix of VGG16 model

All things considered, VGG16 is highly suited for the detecting of breast cancer, such as whether an mammogram is benign or malignant, and aid in achieving high detection accuracy rates. These factors include deep architecture[31], massive on INbreast data set training, reliability to mammogram transformations, and advanced techniques.
Comparison Survey of the Model:

The aim of this research is to contrast the effectiveness of two widely used CNN architectures for the job of breast cancer detection: VGG16, ResNet50 and VGG19. As one of the most common and deadly diseases in the world, breast cancer must be detected early in order to receive an effective course of therapy. In medical image analysis, CNNs have demonstrated encouraging outcomes, including the identification of breast cancer. This study assesses the accuracy, precision, recall, and F1-score of VGG16, VGG19 and ResNet50 models that were trained and evaluated on a dataset of photos related to breast cancer. Computational efficiency issues will also be investigated in order to shed light on how well these models work in real-world clinical contexts.

To compare the binary classification performance of models, evaluation metrics are utilized and summarized[32] in TABLE 1.

Metrics	**VGG16**	**Resnet50**	**VGG19**
Accuracy	0.96	0.52	0.68
Precision	0.94	0.51	0.64
Recall	1.00	1.00	0.63
F1-Score	0.97	0.68	0.63

TABLE 1: Model Comparison

V. CONCLUSION AND FUTURESCOPE

The VGG16 model demonstrates promising potential for detecting cancer in mammograms. Through rigorous evaluation on a dataset of mammogram images, the model achieved an overall accuracy of 96.47%. Additionally, it displayed commendable precision and recall rates, indicate its ability to correctly identify both negative and positive instances of cancerous findings. Furthermore, the confusion matrix analysis revealed that the model effectively distinguished between cancerous and non-cancerous cases, with minimal misclassifications. The majority of instances were correctly classified, underscoring the robustness of the VGG16 architecture for mammogram analysis.

However, despite its notable performance, the model exhibited certain limitations, particularly in cases with subtle or complex features. Further refinement and fine-tuning of the model, possibly through techniques such as data augmentation or transfer learning, could potentially enhance its accuracy and generalization capabilities. Overall, the VGG16 model presents a promising tool for aiding radiologists in the early detection of breast cancer through mammogram analysis. Continued research and development efforts in this domain hold the potential to significantly improve diagnostic accuracy and patient outcomes.

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