

Reducing False Negatives in Breast Cancer Detection by combining Super-Resolution Images with Enhancement Techniques

Vandana Lingampally¹, K. Radhika²

¹Research scholar, Department of CSE, Osmania University, Hyderabad, Telangana, India.

²Professor, Department of IT CBIT, Hyderabad, Telangana, India

Abstract— In an effort to enhance the accuracy of breast cancer diagnosis, the proposed model utilizes super-resolution (SR) images to mitigate the incidence of false negatives. A super resolution image have more pixel density and thereby gives more detailed information about the abnormalities present in the mammogram which will help in deciding whether the abnormality is benign or malignant. To obtain high resolution images FSRCNN and LapSRN models were trained with CBIS-DDSM dataset. High resolution images were generated from trained FSRCNN and LapSRN models. These SR images were subsequently applied to a suite of deep learning models, and the findings indicate that the incorporation of SR images resulted in a significant improvement in the reduction of false negatives.

Keywords— Breast cancer, Super resolution, Deep learning, FSRCNN, LapSRN.

I. INTRODUCTION

The effective diagnosis of breast cancer depends on resolution of mammograms. High resolution images provide high level details which usually lead to high accuracy. High resolution images can be acquired through high radiation dose and more radiation exposure, but this may damage the DNA of the cells. It is possible to obtain high-resolution mammograms using various super resolution techniques without the use of high radiation methods.

A. Super Resolution

Super resolution is the process of increasing the spatial resolution of image by obtaining more finer details from low resolution images with minimum plunge in quality and eliminating the need of alterations to the existing imaging hardware. In 1964 and 1968, respectively, J.L. Harris and J.W. Goodman put forth the fundamental

concept of image super-resolution. This technique aims to enhance the resolution of low-quality or low-resolution images, providing a clearer and more detailed representation of the underlying content.

B. Need of Super Resolution

Super resolution images have more pixel density and thereby have more details in the image. These high resolution(HR) images are required in many fields such as health care-for better diagnosis, video surveillance-for more accurate investigation, astronomy-to extract more authentic information.

C. Goal of Super Resolution

The goal of super-resolution is to enhance the resolution of images to reveal more details and improve the quality of images, without the need for costly hardware upgrades. This technique has a wide range of applications in many fields and has greatly improved the accuracy and usefulness of low-resolution images.

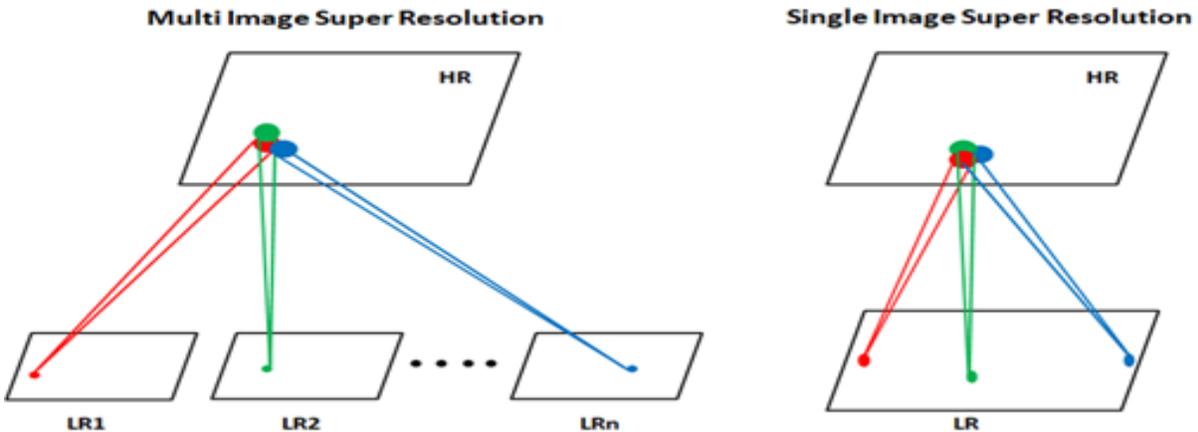
D. Different approaches to obtain Super Resolution Images

Super resolution image can be estimated from one LR image (SISR) or from multiple LR images (MISR)[1, 2]. Latter is complex than first one as obtaining multiple LR images of same scene may not be possible in most of the situations. A number of studies delineate the positive effect of SR images in medical analysis and diagnosis[2,4,5,6]. Diagnosis and classification performance can be enhanced by SR images[2]. Misclassification rates can be reduced using SR images[5]. Fig.1. Presents the idea of SISR and MISR.

E. Techniques to obtain Super Resolution Images

Fig.2. Provides a classification of the different approaches used for generating high-resolution (HR) images from a single low-resolution (LR) image, known as super-resolution (SR). These methods can be categorized into traditional techniques,

Fig.1. presents the idea of MISR and SISR



including interpolation-based, statistics-based, and example-based techniques[3]. Each of these approaches employs various algorithms to enhance the resolution of LR images, thereby improving their visual quality and fidelity. Interpolation-based techniques, such as nearest neighbor, bicubic[8], bilinear[7], and edge-directed interpolation[9], tend to produce blurry edges and introduce aliasing artifacts into the SR image. Similarly, statistics-based techniques and example-based techniques can also result in jagged artifacts and unnecessary details in the SR image.

Several CNN models have been introduced as an alternative to traditional methods for acquiring super-resolution (SR) images. In the realm of convolutional neural network (CNN)-based super-resolution techniques, the upsampling strategy employed in the network can be classified as either direct or progressive. Direct upsampling methods can be further categorized into two types: pre-upsampling and post-upsampling techniques. Each of these methods utilizes specific algorithms to increase the resolution of low-resolution images, with the goal of generating high-resolution images that are visually sharper and more detailed.

Pre-upsampling based SR methods first upsample the LR observation using interpolation techniques, and then use the upsampled image as input to a CNN network that restores the missing high-frequency details. Post-upsampling-based super-resolution methods extract features directly from low-resolution input images and perform upsampling in the final layers of the convolutional neural network (CNN)

using either transposed[11] or sub-pixel[10,23] convolution. This approach aims to generate high-resolution (HR) images that closely match the LR observations while preserving fine details and avoiding artifacts.

On the other hand, progressive SR techniques reconstruct the HR image in several intermediate steps by gradually upsampling the LR input image in increments of a factor of two. This approach enables the network to learn complex features and structures progressively, resulting in improved visual quality and reduced blurring. One of the first and most influential models is SRCNN, which has three layers of CNN: one for extracting patches and features, one for a nonlinear mapping function, and one for constructing SR images. SRCNN is pre-upsampling model that has been applied to a variety of medical images such as mammograms[20], chest CT images[21], and MRI images[22].

FSRCNN[11] is an enhanced version of SRCNN that offers improved speed and accuracy due to its flexible non-linear function. It has two additional layers that help to reduce the number of parameters while maintaining network performance. ESPCN[12], on the other hand, utilizes a sub-pixel convolutional layer to upsample low resolution images, which reduces computational cost compared to traditional interpolation methods used by previous CNN models. EDSR[13] is a modified version of SRResNet that removes unnecessary features, such as range flexibility, to streamline the architecture.

VDSR[14] is a deep convolutional network that utilizes small filters and employs residual learning to

improve training speed. It also utilizes gradient clipping and is trained at high learning rates. SRDenseNet[15] utilizes dense blocks with skip connections to extract high level features, and uses deconvolutional and bottleneck layers during the upscaling process. RDN[16] combines global residual and dense skip connections, while DRCN[17] is based

on similar concepts as VDSR but utilizes recursive supervision and skip connections to prevent exploding or vanishing gradients.

DRRN[18] is a model that uses recursive learning, similar to DRCN, but with a revised Resnet unit as the recursive unit. LapSRN[19] is designed to gradually upscale

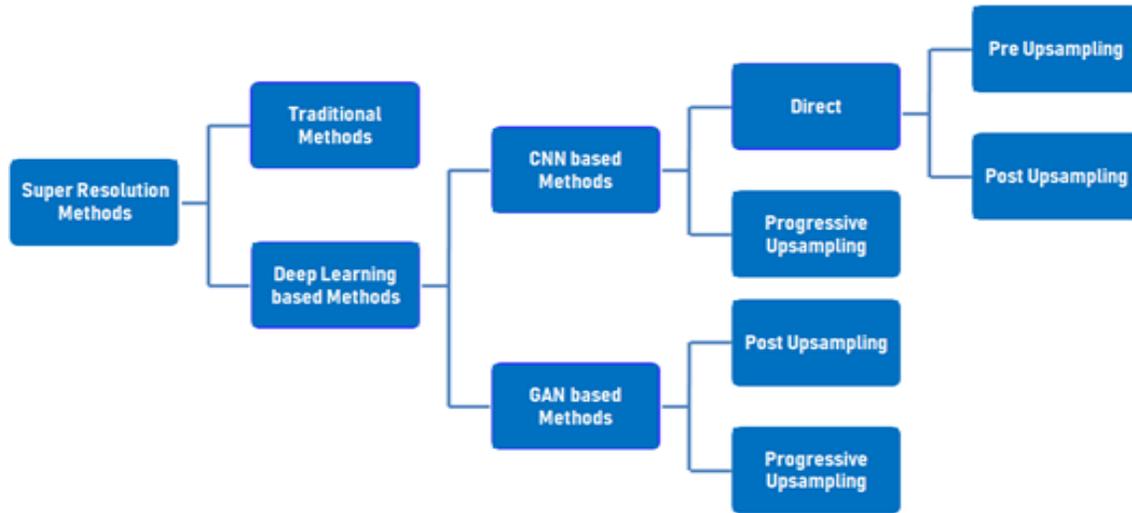


Fig.2. Presents classification of SR models

features. It has two sections: one section extracts and refines features, then passes high frequency details to the other section, which reconstructs the image and learns low frequency information. CNN-based approaches have made significant progress in the field of image super-resolution. Every model has its unique strengths and weaknesses, and the selection of an appropriate model depends on various factors, including the specific application and computational resources available. To achieve high-resolution mammograms in present research work, the advanced FSRCNN and LapSRN models were employed, which have demonstrated impressive results in image super-resolution tasks.

The breast cancer statistics of 2022[37] say that there is 0.5% rise in breast cancer cases annually from 2010 to 2020 and 2.26 million cases recorded in 2020 and it is the leading cause of cancer mortality among females[38]. The mortality rate can be reduced by diagnosing cases correctly i.e., by reducing the number of false negatives. In order to reduce the number of false negatives in detection of breast cancer, this study proposes a DL model. The CBIS-DDSM mammograms are preprocessed and these images are used to train FSRCNN and LapSRN models.

FSRCNN is post-upsampling model and LapSRN is progressive upsampling model. SR images are acquired from trained models. Super resolution images have more pixel density and thereby have more details in the image, from these details more specific features can be extracted which can guide the classifier of the model in detection of breast cancer more accurately by reducing false negatives.

In the following sections of this paper, a summary of previous research in the field will be provided (Section II), the steps taken to create the dataset and describe the proposed model in detail will be outlined (Section III), information on the implementation process will be presented, and the results will be analyzed for their significance (Section IV). Finally, the paper will conclude with a summary of the findings and a discussion of potential future work (Section V).

II. RELATED WORK

Breast cancer is a growing concern in both rural and urban areas of India. According to recent estimates, there were approximately 224,000 new cases of breast cancer in India in 2021. The incidence of this disease

has been on the rise, with an annual increase of 5-6% over the past decade. Unfortunately, the mortality rate for breast cancer in India remains relatively high, with an estimated 138,000 deaths occurring in 2021 alone. As the cancer progresses to higher stages, the chances of survival become increasingly difficult. Unfortunately, more than half of Indian women are diagnosed with stage 3 or 4 breast cancer, highlighting the urgent need for improved detection and treatment methods. To reduce the mortality rate, breast cancer should be detected in early stage so that they can be cured.

A. Breast Cancer identification using Deep learning models

Deep learning models, which are a type of artificial neural network, can learn complex patterns and relationships from large amounts of data. In the context of breast cancer diagnosis, deep learning models can learn to identify subtle patterns and features in medical images that may not be easily discernible to the human eye. This makes deep learning models a valuable tool for assisting radiologists and oncologists in the diagnosis and treatment of breast cancer. Numerous deep learning architectures, including but not limited to AlexNet, ResNet, and VGG models, have been utilized in breast cancer identification. Table 1 provides a summary of the results obtained from selected studies. Additionally, several papers have been published on this topic, and a brief overview of these studies is presented in the text.

2016 Huynh BQ et al. [39] proposed a model to classify breast cancer. The authors used private dataset of mammograms to train and evaluate the model. This model uses 2 methods for feature extraction. First method pre-trained model Alex Net with transfer learning, fine tuning top layers and other method extracting features analytically and for both methods SVM is classifier. Then the output from both the models is combined by soft voting which is considered as an ensemble. Out of 3 models result of ensemble is high(AUC=0.86). In 2018 Pengcheng et al. [40] used pre-trained models (AlexNet, VGGNet, GoogLeNet, ResNet) to detect abnormalities in mammograms. CBIS-DDSM mammograms are augmented and used to train and test the models. Pre-trained models are finetuned and using transfer learning imagenet weights are used. Resnet is used to compute the class

activation maps. In all pre-trained models VGGNet achieved the best accuracy 92.53%.

In 2018 Deniz et al. [41] designed an ensemble with AlexNet and VGG16 pre-trained models which used BreakHis dataset for training and testing the model. The features extracted from fully connected layers of AlexNet and VGG16 are concatenated and given to SVM classifier for classification. They also trained AlexNet with finetuning and compared the results. The AlexNet model performed well with highest accuracy $90.96 \pm 1.59\%$. In 2018 AndrikRampun et al. [42] modified Alexnet by replacing, uses Local Response Normalisation with Batch Normalization, Rectified Linear Unit with Prelu. The CBIS-DDSM was augmented and used for training (70%), validation(20%) and testing(10%). Basing on validation scores they choose 3 best models and combined them as an ensemble and this ensemble model acquired 80.4% of accuracy.

In 2018 Wajahat Nawaz et al. [43] fine tuned AlexNet by modifying and inserting input layer Cnn and Fcn. Histology images patch wise and image wise were used to train and test the model. Accuracy obtained by the model patch wise and image-wise is 75.73% and 81.25%. In 2018, Chennamsetty et al. [44] proposed an ensemble approach that leveraged pre-trained models ResNet-101 and DenseNet-161 to classify histology images. The authors trained and evaluated their models using a dataset that was part of the ICIAR-2018 grand challenge. To normalize the histology data, two methods were employed. The first involved normalizing the data using the mean and standard deviation computed from the same dataset (scheme-1), while the second method normalized the data using the entire training histology dataset (scheme-2). First scheme images are applied on ResNet-101, DenseNet – 161, second scheme images are applied on DenseNet–161. Majority voting is applied on the output of these 3 models. This model has achieved 87.00%.

In 2018 Vesal S et al. [45] finetuned Google's Inception-V3 and ResNet50 pre-trained models. They trained and tested the models using dataset (patchwise and imagewise) which is the part of the BACH 2018 grand challenge. Inception-V3 achieved accuracy 93.40(PW) and 97.08(IW). In 2018 BrancatiN et al. [46] finetuned the Resnet with 34 layers, 50 layers and 101 layers. They trained and tested the models using

dataset which is the part of the BACH 2018 grand challenge. They applied the max probability rule on the output produced by the 3 models. The accuracy achieved by the model is 97.3%. In 2019 Ragab DA et al. [47] finetuned AlexNet pre-trained model, trained and tested this model with DDSM, CBIS-DDSM datasets. The softmax layer is replaced with SVM and experimented with diff kernels(Linear, Quadratic, Cubic, Fine Gaussian, Medium Gaussian, Coarse Gaussian). The model achieved 87.2% highest accuracy with SVM (Medium Gaussian) and CBIS-DDSM dataset.

In 2019 Falconí LG et al. [48] finetuned the pre-trained models MobileNet and NasaNet, trained and tested this models with CBIS-DDSM dataset.They also trained and tested InceptionV3 and Resnet50 models to compare results with MobileNet and NasaNet models. The accuracy achieved by Resnet50 is 78.4 and NasNet is 73.1. In 2019 Khan S et al. [49]

finetuned GoogleNet, VGGNet16, ResNet pre-trained models, and combined the features extracted from them into a fully connected layer for classification. They trained and tested this models with private histology images The accuracy achieved by this model is 97.525%. In 2020 Ridhi A et al. [50] finetuned AlexNet, VGG16, ResNet, GoogLeNet, and InceptionResNet pre-trained models. The output from all these models is concatenated and given to the SVM classifier. These models are trained and tested with CBIS-DDSM dataset. This model achieved 88.00% of accuracy.

In 2020, Saxena et al. [51] conducted a study where they fine-tuned several popular pre-trained models, including AlexNet, VGG16, VGG19, GoogLeNet (Inception-v1), ResNet18, ResNet50, ResNet101, Inception-v3, inception ResNetV2, and SqueezeNet, using a linear

Table - 1. Presents the review of previous research

S.No	Title of the Paper	Author	methods/models	Accuracy %	FNR	FPR
1	Breast cancer detection and classification in digital mammography based on Non-Subsampled Contourlet Transform	Pak F (2015)	(Mini-MIAS), NSCT for feature extraction and Adaboost for classification.	91.43	12.85	6.42
2	A fully integrated computer-aided diagnosis system for digital X-ray mammograms via deep learning detection, segmentation, and classification	Al-Antari MA (2018)	(Inbreast)YOLO for mass detection, FrCN for mass segmentation, CLAHE for enhancement, AlexNet with few changes for etraction and classification.	90.00	2.00	30.00
3	Breast cancer detection using deep convolutional neural networks and support vector machines	Ragab B(2019)	(CBIS-DDSM), threshold and region based methods for segmentation, CLAHE for enhancement, AlexNet for feature extraction and SVM for classification	87.2	13.8	12.3
4	Deep feature-based automatic classification of mammograms	Ridhi A (2020)	(CBIS-DDSM), histogram equalization for enhancement, ensemble of AlexNet, VGG16, ResNet, GoogLeNet, and InceptionResNet for classification	88.00	9.00	15.00
5	Transfer Learning and Fine Tuning in Breast Mammogram Abnormalities Classification on CBIS-DDSM Database	Lenin G. (2020)	(CBIS-DDSM), CLAHE for image enhancement, applied transfer learning / finetuning for pre-trained models VGG, ResNet, NasNet, DenseNet, Inception, MobileNet, Xception, Resnext. VGG16 with finetuning achieved best results	81.58	21.73	15.10
6	Segmentation of masses on mammograms using data augmentation and deep learning.	Zeiser FA (2020)	(CBIS-DDSM), algorithm of Felzenszwalb andHuttenlocher for segmentation, CLAHE for enhancement, UNET models for extraction and classifications	85.95	7.68	19.53
7	Computer-aided diagnosis for breast cancer detection and classification using optimal region growing segmentation withMobileNet model	Rose j (2022)	(Mini-MIAS), region growing methods for segmentation and mobileNet for feature extraction and variational autoencoder for classification.	86.26	6.49	22.32

kernel Support Vector Machine (SVM) as the classifier. The authors evaluated the performance of these models on the BreakHis dataset, which contains breast histopathological images. The experimental results indicated that ResNet50 and ResNet101 outperformed most of the other networks in terms of image classification accuracy. This finding suggests that ResNet models may be particularly well-suited for analyzing histopathological images and could potentially improve the accuracy and reliability of breast cancer diagnosis. In 2021 Hekal AA et al. [52] finetuned AlexNet and ResNet50 pre-trained models, trained and tested these models with CBIS-DDSM dataset. The classifier is SVM with binary nonlinear kernel to represent 4 classes. The accuracy achieved by ResNet-50 is 81.00% and by AlexNet is 90.00%.

In 2021 Khamparia A et al. [53] finetuned AlexNet, VGG16, VGG19, MobileNet and ResNet50 pre-trained models and proposed a model by modifying VGG pre-trained model(MVGG). These models are trained and tested using DDSM dataset. MVGG is trained with dataset(with and without augmentation, with imagenet weights). Accuracy achieved by MVGG model with imagenet weights is 94.3%.

The following papers focus on enhancement techniques applied to mammograms to improve breast cancer identification. In [27], mammograms were enhanced using histogram equalization, histogram stretching, and median filters. In [28], the authors used LCM-CLAHE to enhance mammograms. To avoid losing local information due to over enhancement with CLAHE, they proposed LCM-CLAHE, which provides optimal contrast without losing much local information. In [29], NSCT was used as a pre-processing step to enhance the quality of breast lesions, and a fuzzy driven-based SR technique was implemented to accurately predict intricate structures, detailed patterns, and to remove distortions after identifying the region of interest. In [30], a combination of CLAHE and morphology methods was used to enhance mammograms, so that the noise remaining in the mammogram after applying CLAHE can be removed by the morphology methods.

In [31], FC-CLAHE was used for enhancing mammograms. Unlike CLAHE, which has a fixed clip

value and thus affects all pixel values in the image equally, the authors developed some fuzzy rules to select the clip-limit based on the data present in the mammogram. This method enhanced the image more than CLAHE. In [32], the authors used a pre-trained model DnCNN to enhance mammograms, as it is pre-trained based on the previous learning and will enhance the images. In [33], YOLO was used to detect masses, CLAHE was used for enhancing mammograms, full resolution convolutional network was used for mass segmentation, and CNN was used for the extraction of features and classification. In [34], CLAHE was used for the enhancement of mammograms, and U-Net was used for extraction and classification.

Image classification involves two crucial steps: image pre-processing and application of pre-processed images on selected or designed models for feature extraction and classification. Image pre-processing plays a vital role in achieving accurate results. Table 1 highlights several papers that present details on pre-processing techniques applied to mammograms, the models used for feature extraction and classification, as well as the corresponding results. It is noteworthy that the accuracy, false positive rate, and false negative rate vary significantly among these studies. Despite the implementation of effective pre-processing techniques and models as evident from Table 1, the obtained results still indicate a high incidence of false positive and false negative rates. One plausible explanation for this outcome is that the models lack essential details required to accurately distinguish between malignant and benign cancers.

To obtain a more comprehensive understanding of masses present in mammograms, high-resolution mammograms are crucial. To this end, various models can be utilized, and in this paper, two such models, namely FSRCNN, a post-upsampling SR model, and LapSRN, a progressive upsampling SR model were employed. These models were employed to generate high-resolution mammograms, which were subsequently subjected to feature extraction and classification using EfficientNet models.

Although the enhancement techniques mentioned above have proven effective in improving the quality

of mammograms for breast cancer identification, they may not provide sufficient accuracy when used in isolation. Due to the complexity of breast cancer detection, a combination of techniques is often required to achieve higher quality results. For instance, by combining histogram equalization with super resolution techniques, the resulting mammograms may provide greater clarity on the features of masses, thereby improving the accuracy of breast cancer diagnosis. It is important to continue exploring and integrating various techniques to enhance mammograms and improve the accuracy of breast cancer diagnosis.

The primary objective of my work is to reduce the false negative rate since it poses a significant risk to people's lives. The secondary objective is to balance the false positive rate with the false negative rate which will be the future work. The research in this paper is to achieve first objective.

III. PROPOSED APPROACH

To minimize the occurrence of false negatives, the proposed approach leverages super-resolution (SR) images for abnormality detection in mammograms. Through the application of SR technology, the resolution of mammogram images is improved, leading to enhanced precision in detecting abnormalities. This utilization of SR technology enables a higher level of accuracy in the identification of abnormalities in mammogram images. This section presents an outline of the proposed model.

A. Dataset

The present research employed the CBIS- DDSM dataset. It comprises of mammograms with masses and calcifications. This dataset has mammograms in CC view and MLO view. In total this dataset has 1697 images, among these, 909 images are classified as benign cases while 788 are categorized as malignant cases.

B. Image Preprocessing

Image pre-processing is a sequence of steps to improve the quality of image by enhancing the important features and suppressing the unwanted distortions. The dataset CBIS-DDSM consists of full

mammograms, ROIs and their masks. ROIs are used for this research. Many mammograms have more than one mass and every mass have a separate ROI. Every ROI has CC view and MLO view and every ROI is maintained in separate folder.

First ROI are collected from different folders and combined them into a dataset. The images are in dicom format, they are converted into jpg format. As a first step artifacts are removed from mammograms. The ROIs are of different sizes, as second step all the images are resized to 224 X 224 by maintaining the aspect ratio.

C. Generating super resolution images

The models FSRCNN and LapSRN are trained with mammograms. The trained models are used to generate high resolution mammograms.

Fast Super-Resolution Convolutional Neural Network (FSRCNN)

FSRCNN is developed by addressing the limitations present in SRCNN. In FSRCNN, the computational cost present in SRCNN is reduced and speed of the network has been increased almost by 40 times with better performance than SRCNN. To minimize computational expenses, the FSRCNN model employs the original low-resolution image as input instead of using a bicubic interpolated image. Additionally, the network incorporates a deconvolution layer at the end to facilitate image upsampling. The mapping between LR image and HR image in SRCNN is replaced by a shrinking layer, 4 mapping layers and an expanding layer in FSRCNN and it uses small filter sizes with deep network to improve performance. The number of parameters is reduced from 58,976 to 17,088. If we want to upscale the image to another factor just last deconvolution layer can be finetuned.

FSRCNN consists of a total of five steps. The initial step involves the extraction of features from the original LR image using a smaller filter of size 5. In next step shrinking, the number of features is reduced, so that the network can concentrate on relevant features. In this reduction process they have used 1X1 convolution so that number of parameters can be decreased and thereby the computational cost. The third step is mapping. Instead of using 5X5 filter as in SRCNN, they used 3X3 multiple convolutional layers,

this also reduced the number of parameters and thereby reduction in overfitting problem.

The next step is expanding which is the inverse process of shrinking. Without expanding layer also the network can be formed, but the authors noticed that without expanding layer there was degradation in the performance. The last step is deconvolution, in which the prior features are combined and the image is upsampled with deconvolution kernels. PReLU activation function and MSE cost function and SGD optimizer is used in the network. Fig. 3. Presents the architecture of the FSRCNN model.

Laplacian Pyramid Super-Resolution Network (LapSRN)

LapSRN has been developed to address the following limitations.

1. Previous SR models which were developed have small networks with which complicated mappings cannot be learnt between LR and HR images.
2. L2 loss function which has been used in previous SR models is not able to capture the multi-modal distributions of HR patches.
3. In most of the models only one upsampling step has been used to construct HR images, this creates difficulties when it comes to create HR images of different factors.

This model architecture is designed using Laplacian Pyramid and it constructs HR image in two steps, in first step features are extracted and in next step image is reconstructed. Fig. 4. Presents the architecture of the LapSRN model.

Feature Extraction:

1. A set of convolutional layers extract features from the low resolution image given as input.
2. Using extracted features deconvolution layer upsamples features by factor 2 which is the predicted HR image.
3. Actual HR image is down sampled predicted HR size using bicubic technique.
4. Residual image is constructed from actual and predicted HR images.
5. The predicted image is passed to next level for producing the HR image of factor 4.
6. Residual image is passed to image reconstruction phase.

Image Reconstruction:

1. The deconvolution layer with bilinear kernel upsamples the LR image by factor 2, given as input.
2. Final HR image is obtained by combining residual image and upsampled LR image by element wise summation.
3. This final HR image is given as input to the next level to produce the HR image of factor 4.

Generating HR from LR

Both FSRCNN and LapSRN models are trained on a dataset consisting of paired low-resolution and high-resolution images. These models acquire the ability to map the low-resolution images to their corresponding high-resolution counterparts by effectively recognizing patterns, features, and intricate relationships inherent in the images. After training, the model is applied to the LR images

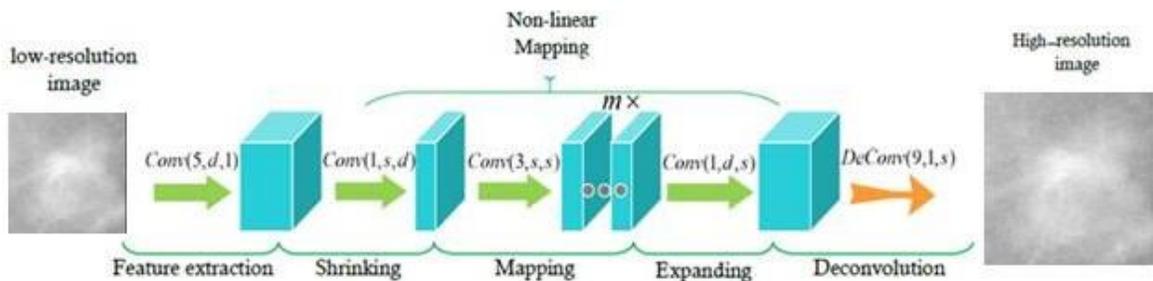


Fig.3. Presents Architecture of FSRCNN Model

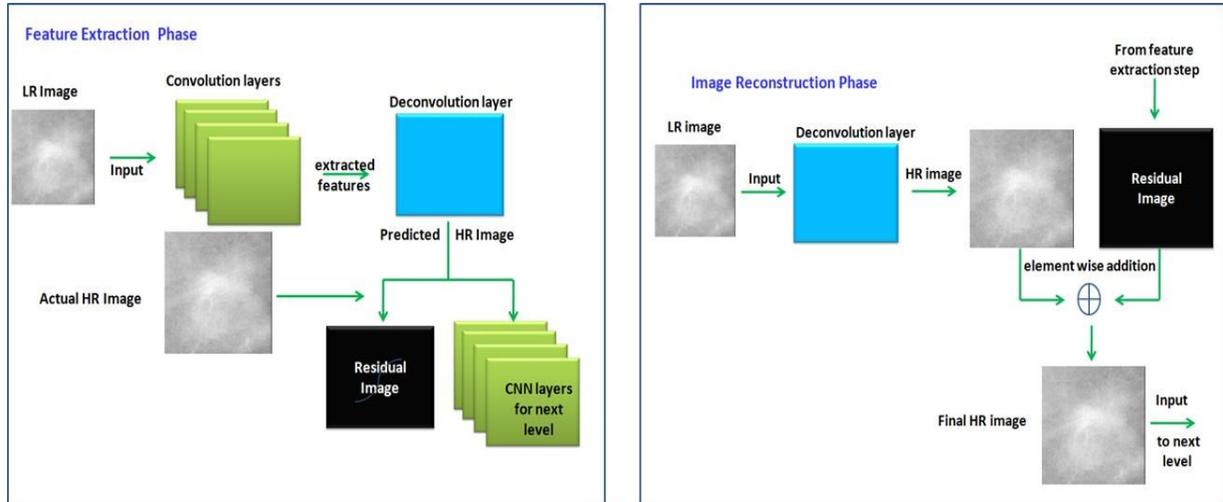


Fig.4. Presents Architecture of LapSRN Model

to generate their HR images. The general process is depicted in Fig. 5.

D. Image Enhancement

Image enhancement is a critical procedure that involves adjusting an image's visual properties to enhance its overall quality, including its contrast, sharpness, and brightness. Even high-resolution images may require enhancement to improve their visual appeal, and this can be achieved through the use of histogram equalization. This technique is effective in redistributing pixel intensity values to increase the image's contrast and brightness, ultimately resulting in a more detailed and informative image. Histogram equalization is a non-linear process that can be applied to high-resolution images to enhance their visual quality and prepare them for further analysis or presentation.

E. Augmentation

Since mammograms are medical images, DL models can utilize the size and shape of masses for diagnosing breast cancer, necessitating the use of specific augmentation techniques. The dataset consists of 909 benign mammograms and 788 malignant

mammograms. To enhance the dataset, each image undergoes rotation at various angles [20°, 40°, 60°, 80°, 100°, 120°, 140°, 160°, 180°, 200°, 220°, 240°, 260°, 280°, 300°, 320°, 340°] shifted vertically and horizontally. By the end of the augmentation process, the total number of images is approximately 34,000.

F. Deep Learning Models

The details of the deep learning models that are used in implementing proposed model. ResNet model has been introduced in 2015 which has a deep architecture. Skip connections used in this model, will overcome the vanishing gradient problem; residual blocks establish an identity mapping to previous outputs in the network to overcome the performance degradation problem which mostly occurs in deep models. It uses mostly 3X3 filters as in VGG models. Efficient Net models were introduced by Google AI in 2019. The main idea introduced in these models is, scaling DNNs in depth, width and resolution uniformly in an effective way, which improves the performance of the model. Taking EfficientNetB0 model as baseline model the team developed a family of Efficient Net models from B1

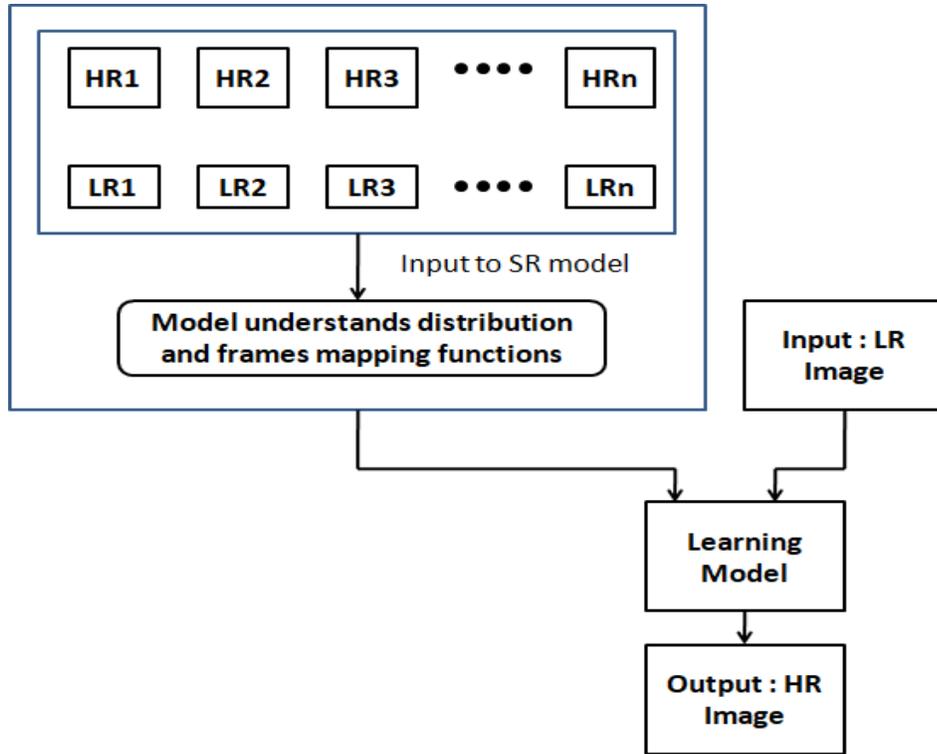


Fig.5. Presents general process to get HR from LR

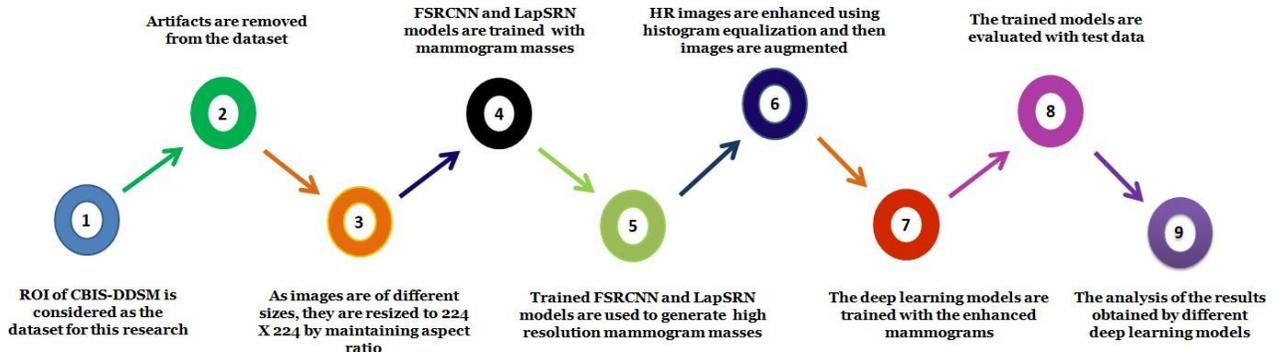


Fig.6. Presents architecture of proposed model

Algorithm : FSRCNN and LapSRN with DL models to reduce FNR

rt-removal of artifacts, rs-resize, seg-segmentation, aug-augmentation, m1, m2-models, hist-histogram equalization, (d1, d2, fsr, lap..are datasets in different stages in preparation of dataset to train models)

Input: Dataset-[CBIS-DDSM mammograms]

Output: [confusion matrix, accuracy, precision, recall]

Step 1: Load the Dataset

Step 2: Preprocessing of Dataset

2.1: $d1 = rt(\text{Dataset})$

Step 3: resizing the mammograms

3.1: $d2 = rs(d1)$

- 3.2 : $HR = rs(d2)$
- 3.3 : $LR = rs(HR)$
- Step 4: Training super resolution models
 - 4.1: $m1 = \text{training}(\text{FSRCNN}, LR, HR)$
 - 4.2: $m2 = \text{training}(\text{LapSRN}, LR, HR)$
- Step 5: Generation of super resolution images
 - 5.1: $fsr = m1(d2)$
 - 5.2: $lap = m2(d2)$
- Step 6: Enhancement
 - 6.1: $fsrh = \text{hist}(fsr)$
 - 6.2: $laph = \text{hist}(lap)$
- Step 7: Augmentation
 - 7.1: $afsrh = \text{aug}(fsrh)$
 - 7.2: $alaph = \text{aug}(laph)$
- Step 8: split datasets($afsrh, alaph$) for training, testing and validation
- Step 9: train the models(resnet50, efficientnetB0 to B7)
 - 9.1 : finetune model parameters(freezing, training layers, tuning parameters like number of epochs, learning rate...)
 - 9.2 : evaluating the proposed models
- Step 10: compute [confusion matrix, accuracy, precision, recall]
- Step 11: evaluation and analysis

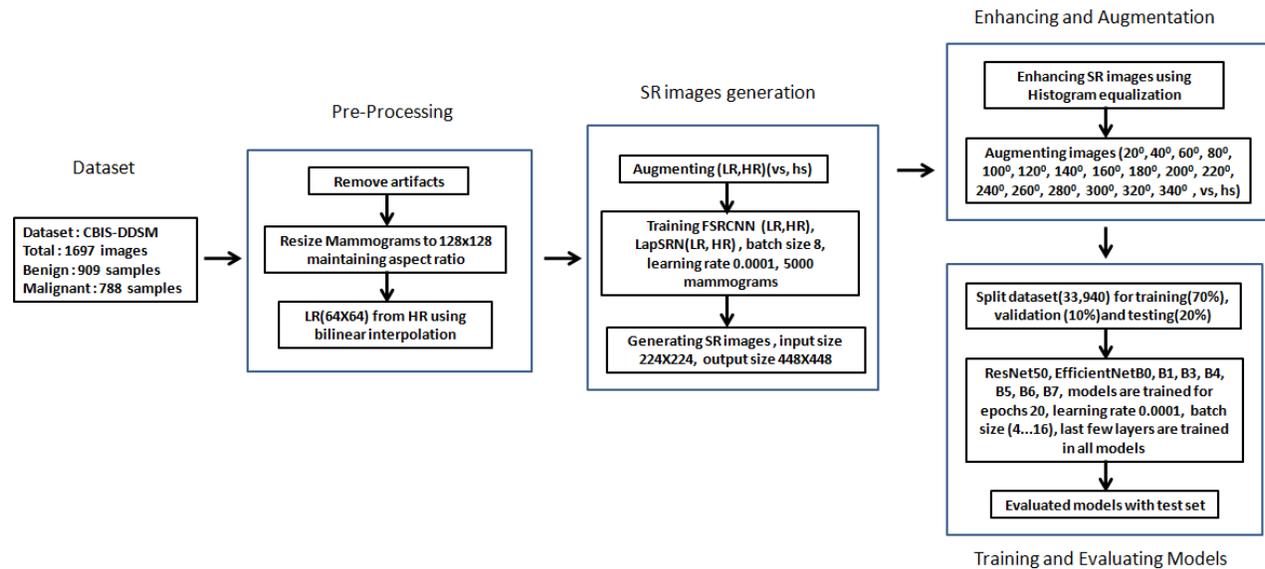


Fig.7. Presents flowchart of proposed model

to B7. These models are designed by combining many techniques, some of them are scaling width, depth and resolution with some constant coefficient, depthwise separable convolutions, SE functions, skip connections.

G. The Proposed Model

The objective of the proposed model is to overcome the constraints of conventional breast cancer detection

methods by employing deep learning techniques to extract more pertinent features from medical images. This model specifically relies on features extracted from a dedicated medical image database containing mammograms, instead of using features from a general image database like Imagenet. Furthermore, it utilizes the features extracted from convolutional layers instead of dense layers. This approach enables

the model to capture a broader spectrum of features from the medical images, as convolutional neural networks (CNNs) are renowned for their effectiveness in extracting features from images. By training the last few layers of the DL models(basing on the size of dataset), we can obtain features that are specific to mammogram masses.

To address the challenge of limited data, one approach is to augment the dataset, thereby expanding the size of the training set. In the context of mammography, the sizes of masses captured in the images are typically small, resulting in potential loss of detail and the introduction of artifacts when resizing the masses for input into a deep learning model. To mitigate these issues, a proposed solution involves utilizing models such as FSRCNN and LapSRN to generate super-resolution images of the masses. These higher-resolution images contain more detailed information due to their increased pixel density. By incorporating these super-resolution images into the training process, the model's accuracy can be improved. This enhancement helps reduce false negatives by enabling the model to more precisely identify and classify the features present in the image. The proposed model is presented through a flowchart in Fig. 7, while Fig. 6. depicts its underlying architecture. Additionally, Algorithm outlines a systematic process for implementing the model.

IV. EXPERIMENTS AND RESULTS

To improve the resolution and clarity of mammogram images, a pre-processing step was performed on the region of interest (ROI) obtained from CBIS-DDSM. This enhanced ROI was then utilized to train two deep learning models: FSRCNN and LapSRN. During the training process, a batch size of 16, a learning rate of 0.0001, and the Adam optimizer were employed. Table 3 displays the PSNR and SSIM values obtained by these models.

The trained models were then used to generate high-resolution images of size 448x448, which were subsequently, enhanced, augmented and then fed into various deep learning models, including ResNet50, EfficientNetB0 to B7. Transfer learning was utilized to fine-tune the last few layers of these deep learning models, as indicated in Table2. To train the deep learning models, 70% of the available data was used

while 10% was reserved for validation purposes. For testing the models, the remaining 20% of the data was allocated. During the training process, the models were trained for a total of 20 epochs using an Adam optimizer with a learning rate of 0.0001. During the training process, the batch size was varied between 4 and 16. This experimental setup allowed for a comprehensive evaluation of the models' performance and ensured that the models were sufficiently trained and validated.

A. Comparing deep learning models for their effectiveness in reducing false negatives using FSRCNN super resolution images

In breast cancer diagnosis, it is crucial to minimize false negatives, as well as false positives. False negatives refer to instances where the diagnostic test incorrectly indicates that the patient does not have breast cancer, despite the presence of the disease. On the other hand, false positives refer to instances where the diagnostic test incorrectly indicates that the patient has breast cancer, when in fact they do not. Minimizing false negatives is especially important in breast cancer diagnosis, as failing to detect the presence of the disease can have serious consequences for the patient's health.

The main aim of this study is to tackle the issue of false negatives in breast cancer diagnosis by leveraging super-resolution mammograms and deep learning models. The SR images obtained from FSRCNN model are applied on ResNet50 and EfficientNetB0 to B7. The results demonstrate that ResNet50, commonly used convolutional neural network architecture, achieved a FNR of 2.8 with super resolution images obtained from FSRCNN model. FNR of 2.8 is very high when compared with other models which are employed in the research. Notably, EfficientNetB7, a recently introduced architecture designed to optimize computational efficiency and accuracy, achieved a significantly lower FNR of 0.47 compared to other models investigated. The findings suggest that the use of EfficientNetB7 may provide an effective strategy for reducing false negatives in breast cancer detection. However, additional research is required to further validate these results and assess the clinical utility of these models in real-world applications.

The data in Table 2. illustrates the number of layers that are trained and that are freezed in every deep learning model used in the research. Table 3. Gives

PSNR and SSIM values obtained by FSRCNN and LapSRN models. Sample HR images generated from LR images using the FSRCNN model are presented in Fig. 8. This study primarily focused on reducing the rate of false negatives in the deep learning models

employed. Table 4 presents the false negative percentages, accuracy, precision, and recall metrics for the various models, with graphical representation in Fig. 10.

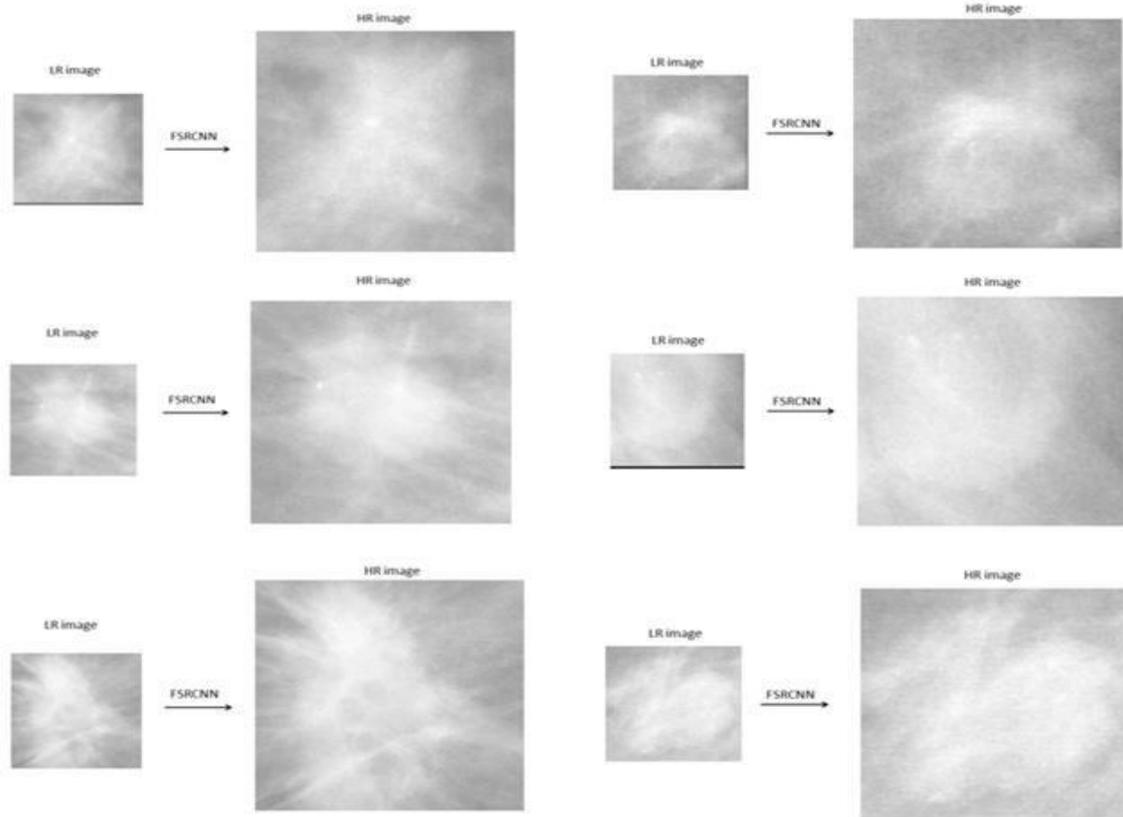


Fig. 8. Presents few samples of generated HR from LR using FSRCNN

From the results, it is evident that while the ResNet model showed poor performance in minimizing false negatives, the EfficientNetB7 model demonstrated exceptional performance in this regard. Furthermore, the confusion matrix (CM) of the EfficientNetB7 model is presented in Fig. 13.

B. Comparing deep learning models for their effectiveness in reducing false negatives using LapSRN super resolution images

Super-resolution images, which are HR images generated from LR inputs, have become an important tool in medical imaging to enhance the accuracy of breast cancer detection. By using super-resolution techniques, it is possible to generate detailed images of breast tissue, which can reveal small lesions and other abnormalities that may be difficult to detect with traditional imaging methods. When these images are

applied on deep learning models, the models will identify the features of benign/malign tumors, in this way there will be reduction in false negative rate and thereby increase in accuracy. The high resolution images are obtained from LapSRN model and then these HR images are applied on ResNet and EfficientNetB0 to B7 models. The false negative percentages, accuracy, precision, and recall metrics for the various models are presented in Table 5, with graphical representation in Fig. 9.

The results demonstrate that while the ResNet model showed poor performance in minimizing false negatives (i.e., 2.0), the EfficientNetB7 model demonstrated exceptional performance (0.28) in this regard. Additionally, the confusion matrix of the EfficientNetB7 model is presented in Fig. 11. Furthermore, sample HR images generated from LR

images using the LapSRN model are presented in Fig. 9.

C. Comparing deep learning models for their effectiveness in increasing accuracy

The superior performance of EfficientNetB7 in breast cancer detection can be attributed to its efficient architecture, which enables it to process super-

resolution images in a more effective and accurate way. Additionally, the use of FSRCNN and LapSRN super-resolution methods enhance the resolution of LR images and improve the quality of the images, which in turn can lead to more accurate diagnosis of breast cancer. EfficientNetB6

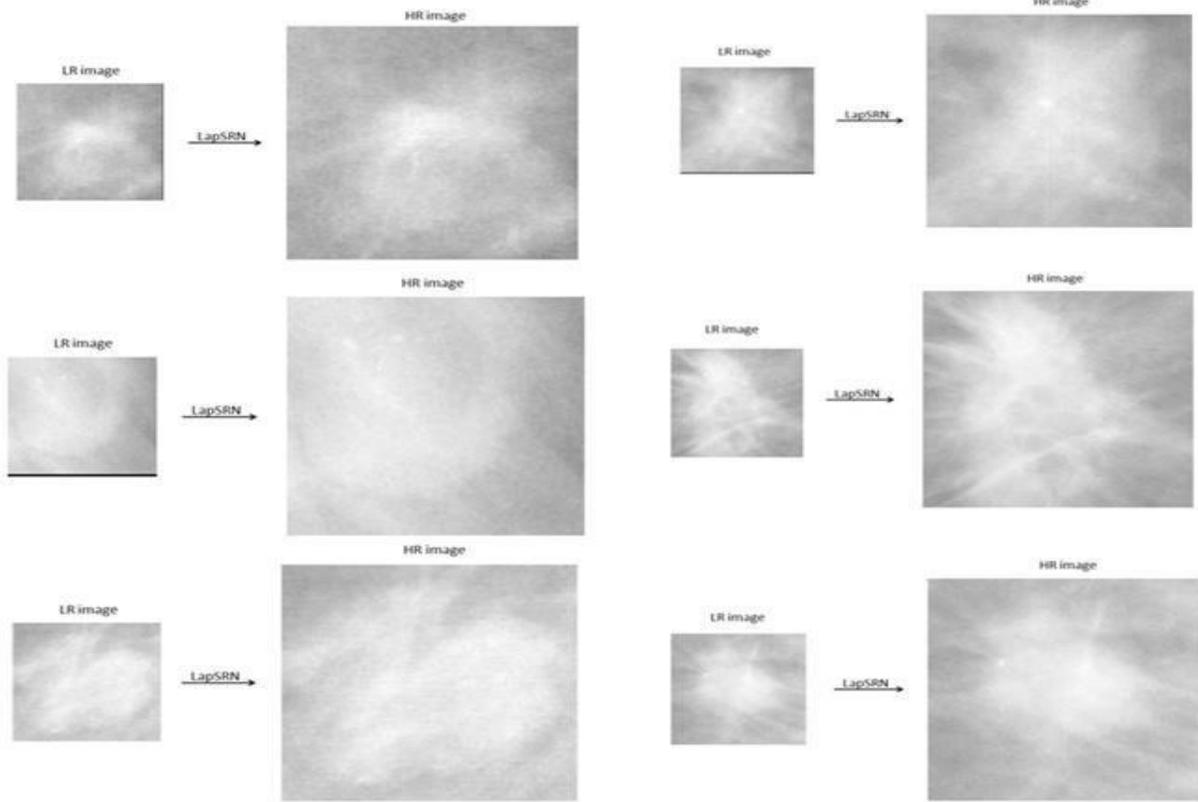


Fig.9. Presents few samples of generated HR from LR using LapSRN

Table - 4. Presents metrics achieved by FSRCNN SR images. Table - 5. Presents metrics achieved by LapSRN SR images .

Super Resolution Images(FSRCNN)				
Models	Accuracy %	Precision %	Recall %	False Negative %
ResNet50	96.51	96.00	97.22	2.80
EfficientNetB0	98.73	99.40	97.87	2.10
EfficientNetB1	98.52	98.95	98.16	1.80
EfficientNetB3	97.25	96.05	98.48	1.50
EfficientNetB4	98.47	98.01	99.04	0.96
EfficientNetB5	99.04	98.90	99.12	0.88
EfficientNetB6	98.36	97.25	99.41	0.59
EfficientNetB7	98.34	97.40	99.53	0.47

Super Resolution Images(LapSRN)				
Models	Accuracy %	Precision %	Recall %	False Negative %
ResNet50	97.89	97.68	97.97	2.00
EfficientNetB0	98.09	98.13	98.10	1.90
EfficientNetB1	98.61	98.91	98.36	1.60
EfficientNetB3	98.13	97.43	98.96	1.00
EfficientNetB4	97.48	96.23	99.08	0.92
EfficientNetB5	98.82	98.41	99.18	0.82
EfficientNetB6	99.18	99.00	99.47	0.53
EfficientNetB7	98.78	97.92	99.72	0.28

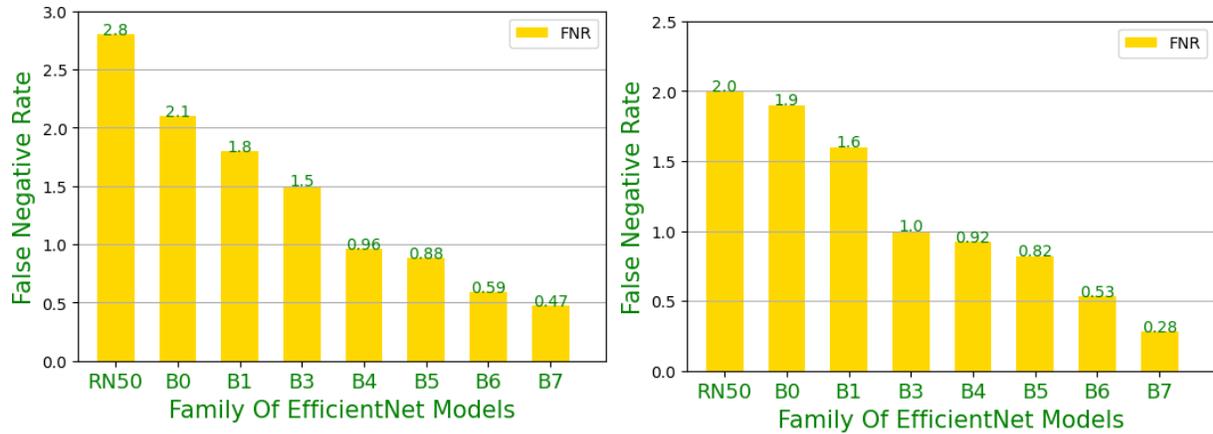


Fig.10. Presents graphical representation of FNR achieved by different DL models using FSRCNN SR images. Fig.11. Presents graphical representation of FNR achieved by different DL models using LapSRN SR images.

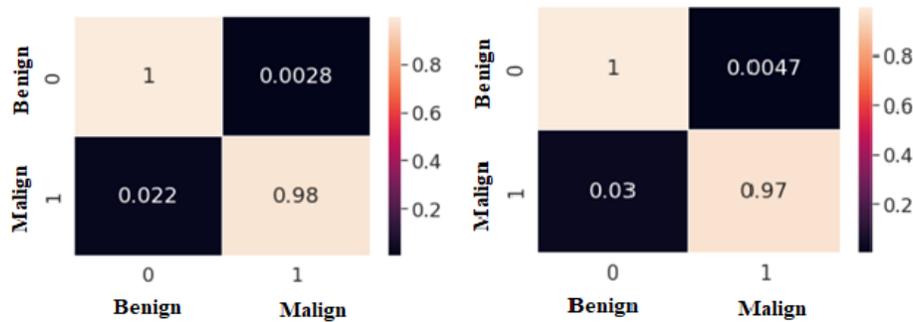


Fig.12. Presents confusion matrix of EfficientNetB7 with LapSRN images. Fig.13. Presents confusion matrix of EfficientNetB7 with FSRCNN images.

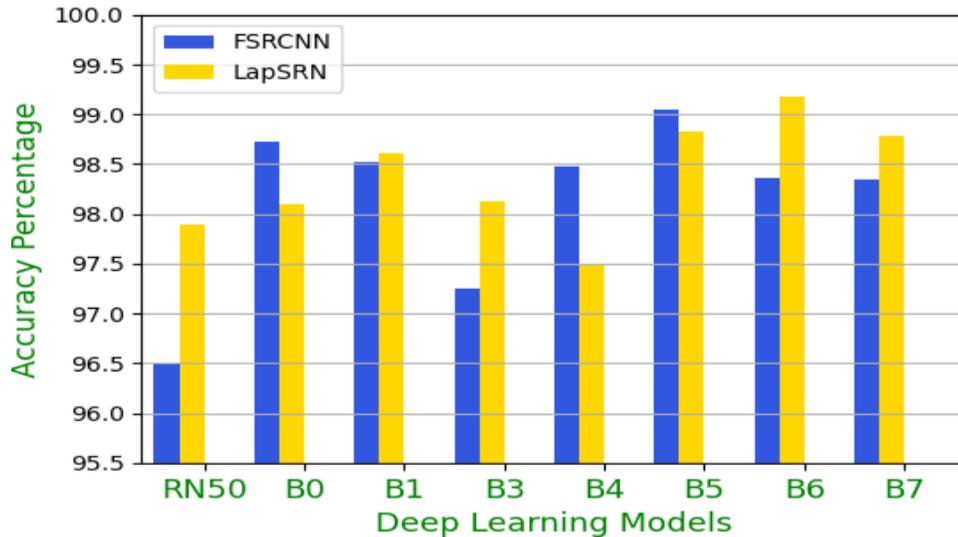


Fig.14. Presents accuracy % achieved by DL models using SR images

has given the highest accuracy with LapSRN images and EfficientNetB5 has given the highest accuracy with FSRCNN images.

The accuracy percentages of various deep learning

models can be seen in Table 4 and Table 5 and the graphical representation is presented in Fig. 14, Table 6 presents the comparison of previous work with the proposed model.

Table - 6. Comparison of previous work with proposed model

S.No	Author (Yr)	DL Model	Accuracy
1	In 2019 Falconí LG[50]	ResNet50	78.40%
2	In 2019 Ragab DA [49]	AlexNet	87.20%
3	In 2021 Hekal AA[54]	AlexNet	90.00%
4	In 2018 Deniz [43]	AlexNet	90.96%
5	In 2018 Pengcheng[42]	VggNet	92.53%
6	In 2018 Vesal S [47]	ResNet	97.30%
7	Our Research	EfficientNetB6	99.18%

D. Comparison of previous work with proposed model

Deep learning models have made notable advancements in the domain of breast cancer detection in recent years. Numerous studies have documented encouraging outcomes by employing diverse deep learning architectures, including AlexNet, VggNet, and ResNet. (presented in Table). For instance, in 2018, Pengcheng et al. achieved an accuracy of 92.53% using VggNet. In the same year, Vesal S. reported an impressive accuracy of 97.30% using ResNet. This research achieved an even higher accuracy in breast cancer detection using the EfficientNet models. The results showed an accuracy of 99.18%, which is a significant improvement over the previous studies.

Additionally, the study was able to reduce the false negative rate (fNR) to 0.28 by combining the EfficientNet models with super-resolution (SR) images from LapSRN. The research demonstrates that the EfficientNet models are highly effective in breast cancer detection and has the potential to significantly improve the accuracy of diagnosis. Moreover, the results show that the combination of deep learning models and advanced imaging techniques such as SR can further enhance the accuracy of breast cancer detection. These findings have important implications for the development of more accurate and reliable breast cancer detection systems in the future.

E. Strategies employed in proposed model to reduce false negative rate

The proposed model to reduce FNR in breast cancer detection utilized several strategies. To enhance decision-making capabilities, HR images were utilized instead of LR ones, enabling the extraction of more pertinent features. This allowed the model to capture more details in the images, which could potentially aid in the detection of subtle abnormalities. Secondly, two CNN models, FSRCNN and LapSRN, were used to produce super-resolution images. These models were utilized to upscale the low-resolution images to higher resolutions, which could enhance the overall image quality and potentially increase the accuracy of the model.

In order to enhance the robustness of the model, the dataset was augmented through the application of various transformations, including flipping and rotating, thereby expanding the diversity of the data. This approach allowed the model to be exposed to different variations of the images, which could help it better generalize to new, unseen data. For training the SR images, EfficientNet models were employed, renowned for their exceptional performance in numerous computer vision tasks, thus ensuring state-of-the-art results. This decision was made to ensure that the model could capture complex patterns and features in the images, potentially leading to better detection accuracy.

The other strategy used is fine-tuning, which is a crucial step in the training of deep learning models. In this research, fine-tuning the last three blocks of the EfficientNet models allowed the model to adjust its weights and biases to better fit the specific dataset being used. This process can lead to significant improvements in the model's accuracy, as it is essentially refining the model's decision-making capabilities based on the characteristics of the data. By fine-tuning the model, the network can learn to better distinguish between benign and malignant lesions in breast images, ultimately leading to a more effective and reliable detection system.

Overall, the proposed strategies used in the model were aimed at improving the accuracy of breast cancer detection by reducing the false negative rate. The utilization of high-resolution images, super-resolution techniques, data augmentation, state-of-the-art deep learning models, and fine-tuning were all employed to achieve this goal.

V. CONCLUSION AND FUTURE WORK

In summary, the reviewed literature suggests that prior studies on breast cancer detection utilized pre-processed and enhanced mammograms, which were then analyzed using deep learning models like AlexNet, VGG and many more. Despite the application of advanced techniques and models, however, these studies reported high false negative rates and variations in their results. To address this limitation, a novel model was proposed in this study. The proposed model utilizes high-resolution mammograms generated by two CNN models, FSRCNN and LapSRN, which contain more detailed information about breast tissue abnormalities. These high-resolution mammograms were then analyzed using ResNet and EfficientNet models, resulting in a significant decrease in false negative rates and an increase in overall accuracy. Based on the findings of this study, it appears that using high-resolution mammograms could be a promising approach to enhance the accuracy of breast cancer detection by providing deep learning models with more detailed information about abnormalities in breast tissue. Further research is necessary to assess the effectiveness of this approach in clinical settings and potentially improve patient outcomes.

As a potential avenue for future research, it may be beneficial to investigate the utilization of Generative Adversarial Networks (GANs) to generate SR images. GANs are known to be highly specialized in generating SR images with enhanced details and features. This approach could potentially reduce both the false negative and false positive rates and balance both, leading to more accurate diagnoses. GANs can also be used as a means of synthesizing training data in situations where data availability is limited. This approach could prove particularly useful in contexts such as medical imaging, where data can be difficult to obtain due to various constraints. By leveraging GANs to generate synthetic data, it may be possible to augment existing datasets and improve the performance of deep learning models in these challenging environments. Additionally, the use of GANs in this manner could facilitate the development of robust models that are able to generalize well to new data, further enhancing the utility and applicability of these approaches.

VI. REFERENCES

- [1] Arai K, Kapoor S. (2019). Advances in computer vision. Conference proceedings CVC, (p. 104).
- [2] Wang Z, Chen J, Hoi SC. (2020). Deep learning for image super-resolution: A survey. IEEE transactions on pattern analysis and machine intelligence, (pp. 3365-87).
- [3] Zamzmi G, Rajaraman S, Antani S. (2020). Accelerating super-resolution and visual task analysis in medical images. Applied Sciences, (p. 4282).
- [4] Zheng J, Fuentes O, Leung MY. (2010). Super-resolution of mammograms. In 2010 IEEE Symposium on Computational Intelligence in Bioinformatics and Computational Biology, (pp. 1-7).
- [5] Li X, Fu W. (2019). Regularized super-resolution restoration algorithm for single medical image based on fuzzy similarity fusion. EURASIP Journal on Image and Video Processing, (p. 83).
- [6] Xu L, Zeng X, Huang Z, Li W, Zhang H. (2020). Low-dose chest X-ray image super-resolution using generative adversarial nets with spectral normalization. Biomedical Signal Processing and Control, (p. 101600).

- [7] Lukin A, Krylov AS, Nasonov A. (2006). Image interpolation by super-resolution. In Proceedings of GraphiCon 2006, (pp. 239-242).
- [8] Keys R. (1981). Cubic convolution interpolation for digital image processing. IEEE transactions on acoustics, speech, and signal processing, (pp. 1153-60).
- [9] Li X, Orchard MT. (2001). New edge-directed interpolation. IEEE transactions on image processing, (pp.1521-7).
- [10] Zhou F, Yang W, Liao Q. (2012). Interpolation-based image super-resolution using multisurface fitting. IEEE Transactions on Image Processing, (pp. 3312-3318).
- [11] Dong C, Loy CC, Tang X. (2016). Accelerating the super-resolution convolutional neural network. In European Conference on Computer Vision, Springer, (pp. 391-407).
- [12] Shi W, Caballero J, Huszár F, Totz J, Aitken AP, Bishop R, Rueckert D, Wang Z. (2016). Real-time single image and video super-resolution using an efficient sub-pixel convolutional neural network. Proceedings of the IEEE conference on computer vision and pattern recognition, (pp. 1874-1883).
- [13] Lim B, Son S, Kim H, Nah S, Mu Lee K. (2017). Enhanced deep residual networks for single image super-resolution. In Proceedings of the IEEE conference on computer vision and pattern recognition workshops, (pp. 136-144).
- [14] Kim J, Lee JK, Lee KM. (2016). Accurate image super-resolution using very deep convolutional networks. Proceedings of the IEEE conference on computer vision and pattern recognition 2016, (pp. 1646-1654)..
- [15] Tong T, Li G, Liu X, Gao Q. (2017). Image super-resolution using dense skip connections. In Proceedings of the IEEE international conference on computer vision 2017, (pp. 4799-4807).
- [16] Zhang Y, Tian Y, Kong Y, Zhong B, Fu Y. (2018). Residual dense network for image super-resolution. In Proceedings of the IEEE conference on computer vision and pattern recognition 2018, (pp. 2472-2481).
- [17] Kim J, Lee JK, Lee KM. (2016). Deeply-recursive convolutional network for image super-resolution. In Proceedings of the IEEE conference on computer vision and pattern recognition 2016, (pp. 1637-1645).
- [18] Tai Y, Yang J, Liu X. (2017). Image super-resolution via deep recursive residual network. In Proceedings of the IEEE conference on computer vision and pattern recognition 2017, (pp. 3147-3155).
- [19] Lai WS, Huang JB, Ahuja N, Yang MH. (2017). Deep laplacian pyramid networks for fast and accurate super-resolution. In Proceedings of the IEEE conference on computer vision and pattern recognition 2017 (pp. 624-632).
- [20] Umehara K, Ota J, Ishida T. (2017). Super-resolution imaging of mammograms based on the super-resolution convolutional neural network. Open Journal of Medical Imaging, (pp. 180-95).P. Tay and J. Havlicek, "Image Watermarking Using Wavelets", in *Proceedings of the 2002 IEEE*, pp. II.258 – II.261, 2002.
- [21] Umehara K, Ota J, Ishida T. (2018). Application of super-resolution convolutional neural network for enhancing image resolution in chest CT. Journal of digital imaging, (pp. 441-50).
- [22] Plenge E, Poot DH, Bernsen M, Kotek G, Houston G, Wielopolski P, van der Weerd L, Niessen WJ, Meijering E. (2012). Super-resolution methods in MRI: can they improve the trade-off between resolution, signal-to-noise ratio, and acquisition time? Magnetic resonance in medicine, (pp. 1983-93).
- [23] W. Shi, J. Caballero, F. Huszar, J. Totz, A. P. Aitken, R. Bishop, D. Rueckert, and Z. Wang, "Real-time single image and video super-resolution using an efficient sub-pixel convolutional neural network," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, (pp. 1874–1883).
- [24] Ledig C, Theis L, Huszár F, Caballero J, Cunningham A, Acosta A, Aitken A, Tejani A, Totz J, Wang Z, Shi W. (2017). Photo-realistic single image super-resolution using a generative adversarial network. In Proceedings of the IEEE conference on computer vision and pattern recognition 2017, (pp. 4681- 4690).
- [25] Harris JL. (1964). Diffraction and resolving power. JOSA, (pp. 931-6).P. Kumswat, Ki. Attakitmongcol and A. Striaew, "A New Approach for Optimization in Image Watermarking by Using Genetic Algorithms", *IEEE Transactions on Signal Processing*, Vol. 53, No. 12, pp. 4707-4719, December, 2005.

- [26] Goodman JW, Knight GR. (1968). Effects of film nonlinearities on wavefront-reconstruction images of diffuse objects. *JOSA*, (pp. 1276-83).
- [27] Langarizadeh M, Mahmud R, Ramli AR, Napis S, Beikzadeh MR, Rahman WE. (2011). Improvement of digital mammogram images using histogram equalization, histogram stretching and median filter. *Journal of medical engineering & technology*, (pp. 103-8).
- [28] Mohan S, Ravishankar M. (2012). Modified contrast limited adaptive histogram equalization based on local contrast enhancement for mammogram images. In *International conference on advances in information technology and mobile communication*, (pp. 397-403).
- [29] Pak F, Kanan HR, Alikhassi A. (2015). Breast cancer detection and classification in digital mammography based on Non-Subsampled Contourlet Transform (NSCT) and Super Resolution. *Computer methods and programs in biomedicine*, (pp. 89-107).
- [30] Kharel N, Alsadoon A, Prasad PW, Elchouemi A. (2017). Early diagnosis of breast cancer using contrast limited adaptive histogram equalization (CLAHE) and Morphology methods. In *2017 8th International Conference on Information and Communication Systems*, (pp. 120-124).
- [31] Jenifer S, Parasuraman S, Kadirvelu A. (2016). Contrast enhancement and brightness preserving of digital mammograms using fuzzy clipped contrast-limited adaptive histogram equalization algorithm. *Applied Soft Computing*, (pp.167-77).
- [32] Singla C, Sarangi PK, Sahoo AK, Singh PK. (2022). Deep learning enhancement on mammogram images for breast cancer detection. *Materials Today: Proceedings*, (pp. 3098-104).
- [33] Al-Antari MA, Al-Masni MA, Choi MT, Han SM, Kim TS. (2018). A fully integrated computer-aided diagnosis system for digital X-ray mammograms via deep learning detection, segmentation, and classification. *International Journal of Medical Informatics*, (pp. 44-54).
- [34] Zeiser FA, da Costa CA, Zonta T, Marques N, Roehe AV, Moreno M, da Rosa Righi R. (2020). Segmentation of masses on mammograms using data augmentation and deep learning. *Journal of digital imaging*, (pp. 858-68).
- [35] Falconi LG, Pérez M, Aguilar WG, Conci A. (2020). Transfer learning and fine tuning in breast mammogram abnormalities classification on CBIS-DDSM database. *Adv. Sci. Technol. Eng. Syst.*, (pp. 154-65).
- [36] Dafni Rose J, VijayaKumar K, Singh L, Sharma SK. (2022). Computer-aided diagnosis for breast cancer detection and classification using optimal region growing segmentation with MobileNet model. *Concurrent Engineering*, (pp. 181-9).
- [37] Giaquinto AN, Sung H, Miller KD, Kramer JL, Newman LA, Minihan A, Jemal A, Siegel RL. (2022). Breast cancer statistics, 2022. *CA: A Cancer Journal for Clinicians*, (pp. 524-41).
- [38] Wilkinson L, Gathani T. (2022). Understanding breast cancer as a global health concern. *The British Journal of Radiology*, (p. 20211033).
- [39] Huynh BQ, Li H, Giger ML. (2016). Digital mammographic tumor classification using transfer learning from deep convolutional neural networks. *Journal of Medical Imaging*, (p. 034501).
- [40] Xi P, Shu C, Goubran R. (2018). Abnormality detection in mammography using deep convolutional neural networks. In *2018 IEEE International Symposium on Medical Measurements and Applications*, (pp. 1-6).
- [41] Deniz E, Şengür A, Kadiroğlu Z, Guo Y, Bajaj V, Budak Ü. (2018). Transfer learning based histopathologic image classification for breast cancer detection. *Health information science and systems*, (pp. 1-7).
- [42] Rampun A, Scotney BW, Morrow PJ, Wang H. (2018). Breast mass classification in mammograms using ensemble convolutional neural networks. In *2018 IEEE 20th International Conference on e-Health Networking, Applications and Services*, (pp. 1-6).
- [43] Nawaz W, Ahmed S, Tahir A, Khan HA. (2018). Classification of breast cancer histology images using AlexNet. In *International conference image analysis and recognition 2018*, (pp. 869-876).
- [44] Chennamsetty SS, Safwan M, Alex V. (2018). Classification of breast cancer histology image using an ensemble of pre-trained neural networks. In *International conference image analysis and recognition 2018*, (pp. 804-811).
- [45] Vesal S, Ravikumar N, Davari A, Ellmann S, Maier A. (2018). Classification of breast cancer histology images using transfer learning. In

- International conference image analysis and recognition 2018, (pp. 812-819).
- [46] Brancati N, Frucci M, Riccio D. (2018). Multi-classification of breast cancer histology images by using a fine-tuning strategy. In International conference image analysis and recognition, (pp. 771-778).
- [47] Ragab DA, Sharkas M, Marshall S, Ren J. (2019). Breast cancer detection using deep convolutional neural networks and support vector machines. PeerJ, (p. e6201).
- [48] Falconí LG, Pérez M, Aguilar WG. (2019). Transfer learning in breast mammogram abnormalities classification with MobileNet and NASNet. In 2019 International Conference on Systems, Signals and Image Processing, (pp. 109-114).
- [49] Khan S, Islam N, Jan Z, Din IU, Rodrigues JJ. (2019). A novel deep learning-based framework for the detection and classification of breast cancer using transfer learning. Pattern Recognition Letters, (pp. 1-6).
- [50] Ridhi A, Rai PK, Balasubramanian R. (2020). Deep feature-based automatic classification of mammograms. Medical and Biological Engineering and Computing, (pp. 1199-1211).
- [51] Saxena S, Shukla S, Gyanchandani M. (2020). Pre-trained convolutional neural networks as feature extractors for diagnosis of breast cancer using histopathology. International Journal of Imaging Systems and Technology, (pp. 577-91).
- [52] Hekal AA, Elnakib A, Moustafa HE. (2021). Automated early breast cancer detection and classification system. Signal, Image and Video Processing, (pp. 1-9).
- [53] Khamparia A, Bharati S, Podder P, Gupta D, Khanna A, Phung TK, Thanh DN. (2021). Diagnosis of breast cancer based on modern mammography using hybrid transfer learning. Multidimensional systems and signal processing, (pp. 747-65).