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High Resolution Image for Breast Cancer Classification Using CNN and LSTM with Unet and GAN Model

Dr. Santhi Baskaran , Logaprasanna.M , Raj Arvind.S , Hariprasath.E Sriram.M
Department of Information Technology
Puducherry Technological University
Puducherry,India
santhibaskaran@ptuniv.edu.in

***Abstract*— Breast cancer is one the most critical disease and suffered by many people around the world especially women. While the rates of breast cancer are greater among women in more developed countries, they are rising in almost every location throughout the world. This cancer can be cured if it is diagnosed at preliminary stage. Malignant and benign are two types of breast cancer found in case of tumor. Malignant tumors are so dangerous and their rate of growth is comparatively much higher than benign tumors. Proper classification of breast cancer is important to proceed with best treatment for patients. This project aims to improve the classification accuracy of breast cancer using the mammograms of breast cancer patients. Using deep learning method and machine learning methods there are numerous studies for this purpose. This paper proposes, Hybrid deep learning technique to classify breast cancer with image enhancement algorithm. The mammograms of breast cancer patients have been pre-processed using GAN model for converting low pixel into High resolution images thus intern increase the accuracy in classification. Data augmentation is implemented to improve scalability. CNNs can automatically classify breast mammograms into categories. Despite their demonstrated utility, CNNs with LSTM have not been widely used in breast mammogram classification and with validation. Implementation CNN with LSTM for classification of breast cancer with validation of model using U-net to improve the accuracy of classification. classifiers are examined on the basis of accuracy, precision, recall, f1-score parameters etc. The experimental results prove the quality and efficiency of the proposed method in relation to traditional models.**

Keywords—CNN-LSTM, GAN, U-NET

I. INTRODUCTION

In 2020, there were 2.3 million women diagnosed with breast cancer and 685 000 deaths globally. As of the end of 2020, there were 7.8 million women alive who were diagnosed with breast cancer in the past 5 years, making it the world's most prevalent cancer. There are more lost disability-adjusted life years (DALYs) by women to breast cancer globally than any other type of cancer. Breast cancer occurs in every country of the world in women at any age after puberty but with increasing rates in later life.

Approximately half of breast cancers develop in women who have no identifiable breast cancer risk factor other than gender (female) and age (over 40 years). Certain factors increase the risk of breast cancer including increasing age, obesity, harmful use of alcohol, family history of breast cancer, history of radiation exposure, reproductive history (such as age that menstrual periods began and age at first pregnancy), tobacco use and postmenopausal hormone therapy.

Survival of breast cancer for at least 5 years after diagnosis ranges from more than 90% in high-income countries, to 66% in India and 40% in South Africa. Early detection and treatment has proven successful in high-income countries and should be applied in countries with limited resources where some of the standard tools are available. Reducing global breast cancer mortality by 2.5% per year would avert 25% of breast cancer deaths by 2030 and 40% by 2040 among women under 70 years of age. The three pillars toward achieving these objectives are: health promotion for early detection; timely diagnosis; and comprehensive breast cancer management.

Breast cancer most commonly presents as a painless lump or thickening in the breast. It is important that women finding an abnormal lump in the breast consult a health practitioner without a delay of more than 1-2 months even when there is no pain associated with it. Seeking medical attention at the first sign of a potential symptom allows for more successful treatment. By providing public health education to improve awareness among women of the signs and symptoms of breast cancer and, together with their families, understand the importance of early detection and treatment, more women would consult medical practitioners when breast cancer is first suspected, and before any cancer present is advanced. This is possible even in the absence of mammographic screening that is impractical in many countries at the present time. Public education needs to be combined with health worker education about the signs and symptoms of early breast cancer so that women are referred to diagnostic services when appropriate.

Rapid diagnosis needs to be linked to effective cancer treatment that in many settings requires some level of specialized cancer care. By establishing centralized services in a cancer facility or hospital, using breast cancer as a model, treatment for breast cancer may be optimized while improving management of other cancers.

II. List Of Abbrevations and a AND ACRONYMS

AI	- Artificial Intelligence
API	- Application Programming Interface
CIRC	- Well-Defined/Circumscribed Masses
CNN	- Convolutional Neural Network
EDSR	- Enhanced Deep Residual Network
ELM	- Extreme Learning Machine
FN	- False Negative
FP	- False Positive
GAN	- Generative Adversarial Networks
LeakyReLU	- Leaky Rectified Linear Unit
LSTM	- Long Short-Term Memory
MDCM	-Multi-Scale Dilated Convolutions Module
MF U-Net	- Multi-Scale Fusion U-Net
MIAS	- Mammographic Image Analysis Society
MISC	- ill-defined masses
POI	- Points of interest
ROI	- Region of interest
SVM	- Support Vector Machine
TN	- True Negative
TP	- True Positive
U-net	-Convolutional Networks for Biomedical Image
VGG	- Visual Geometry Group
WFM	- Wavelet Fusion Module

III. Literature Survey

Pramit Brata Chanda; Subir Kumar Sarkar; Detection and Classification Technique of Breast Cancer Using Multi Karnal SVM Classifier Approach. [1]In this paper, Detection and Classification Technique of Breast Cancer Using Multi Karnal SVM Classifier Approach is done, the segmentation method is used. Ostu thresholding method is used for segmentation. For classification SVM- Support Vector Machine is used as classifier. The limitations are necessary points of interest details are omitted during Image Segmentation in this method and the model perform Less accurate with large dataset.

Rui Man; Ping Yang; And Bowen Xu; Classification of Breast Cancer Histopathological Images Using Discriminative Patches Screened by Generative Adversarial Networks. [2]In this paper, A Review on Recent Progress in Thermal Imaging and Deep Learning Approaches for Breast Cancer Detection histopathological image are used. AnoGAN – Unsupervised anomaly detection technique with Generative adversarial network is used. Dense Net is use for classification. The proposed method is suitable only for low level magnification images. It doesn’t provide efficient result in normal mammogram images.

Sanket Agrawal, Rucha Rangnekar, Divye Gala, Sheryl Paul and Dr. Dhananjay Kalbande Detection of Breast Cancer from Mammograms using a Hybrid Approach of Deep Learning and Linear Classification. [3]In this paper, breast cancer detection is done from mammogram images using a hybrid approach of deep learning method and Linear Classification. The techniques

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which are used her are CLAHE for image pre-processing. VGG16, based on Convolutional Neural Network is used for features extraction. K-Nearest Neighbors, Decision Tree, Gradient Boosting are used as classifiers. The limitation of the technique used here is VGG16 which does not perform efficiently with grayscale images therefore lacks in accuracy.

Zhiqiong Wang; Mo Li; Huaxia Wang; Hanyu Jiang; Yudong Yao; Hao Zhang, And Junchang Xin; Breast Cancer Detection Using Extreme Learning Machine Based on Feature Fusion with CNN Deep Features. [5]In this paper, Breast Cancer Detection Using Extreme Learning Machine Based on Feature Fusion with CNN Deep Features. The technique used here are CNN – Convolution Neural Network, unsupervised Extreme Learning Machine – ELM is used for clustering. The limitations are ELM consume more time for testing. Binary classification can only be done using this. ELM consumes more time during the testing phase.

Roslidar Roslidar; Aulia Rahman; Rusdha Muharar; Muhammad Rizky Syahputra; Fitri Arnia; Maimun Syukri; Biswajeet Pradhan and Khairul Munadi; A Review on Recent Progress in Thermal Imaging and Deep Learning Approaches for Breast Cancer Detection. [6]In this paper, Review on Recent Progress in Thermal Imaging and Deep Learning Approaches for Breast Cancer Detection thermal images are used and deep learning techniques like NNs -Neural Networks, CNN -Central Neural Network models are used. The limitation in here is feature extraction is done on whole image, ROI – Region of interest is not used.

Jingyao Li; Lianglun Cheng; Tingjian Xia; Haomin Ni, And Jiao Li;,Multi-Scale Fusion U-Net for the Segmentation of Breast Lesions. [10] In this paper Multi-Scale Fusion U-Net for the Segmentation of Breast Lesions the technique which are used here are Multi-Scale Fusion U-Net (MF U-Net), the Wavelet Fusion Module (WFM), The Multi-Scale Dilated Convolutions Module (MDCM). The Wavelet Fusion Module (WFM) proposed in this model doesn't provide good segmentation accuracy. The above-mentioned papers have been surveyed and the advantages and limitations of each of the papers have been identified. The major limitation in the proposed model is WFM proposed in the model doesn't provide good segmentation accuracy.

IV. PROPOSTED SYSTEM

Breast cancer constitutes a significant threat to women's health and is considered the second leading cause of their death. Breast cancer is a result of abnormal behavior in the functionality of the normal breast cells. Therefore, breast cells tend to grow uncontrollably, forming a tumor that can be felt like a breast lump. Early diagnosis of breast cancer is proved to reduce he death by providing a better chance of identifying a suitable treatment. Deep learning Algorithms plays a key role in healthcare systems by assisting physicians in diagnosing early, better, and treating various diseases. For achieving the early detection of reast cancer, this project proposes a GAN method for image enhancement used with data augmentation and the features are extracted from the images.

Hybrid deep learning technique is proposed for classification as every classification approach has its own advantages and disadvantages. The CNN-LSTM model based two-level top-down hierarchical approach and combined with U-NET for breast cancer detection and classification into three classes: normal, benign, and malignant, using the Mammographic Image Analysis Society (MIAS) mammography dataset.

A. Dataset

The Mammographic Image Analysis Society (MIAS) mammography dataset. The dataset consists of information text file and 322 pgm (Portable Gray Map) mammogram images files.

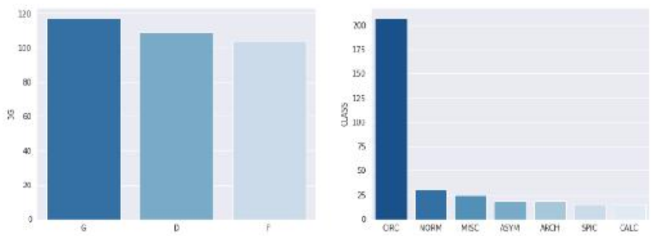

Fig.1. The Architecture Diagram of the Proposed System

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The Dataset comprises of 7 columns with total of 18 attributes with the ID number being the first column and Character of background tissue(F - Fatty , G - Fatty-glandular, D - Dense-glandular) being the second column, Class of abnormality present(CALC - Calcification, CIRC - Well-defined/circumscribed masses, SPIC - Spiculated masses, MISC - Other, ill-defined masses, ARCH - Architectural distortion, ASYM - Asymmetry, NORM - Normal, the diagnosis outcome (0-benign and 1-malignant) being the fourth column and x, y image-coordinates of center of abnormality being the fourth and fifth column respectively and the approximate radius of abnormality as the seventh column.

B. GAN Model

The images from dataset are the input to GAN model. The GAN model consists of Discriminator, Generator. It consists of Dense, LeakyReLu, BatchNormalization layers. At the Generator function the sequential() is used, The Sequential model API is a way of creating deep learning models where an instance of the Sequential class is created and model layers are created and added to it. The dense layer (256, input_dima=100) is added to the model. The LeakyReLU layer is added to the model with (alpha=0.2), then BatchNormalization is used with (momentum=0.8). Again, the same layers are added with constant alpha and momentum along with increasing dense layer. At the final dense layer is added with the activation of ‘tanh’. The summary () is used to get the information about the model.

At the Discriminator function the sequential() is used, the flaten layer (input_shape=image shape) is added to the model. Here the dense layer with unit of 512 and 256 is added with LeakyReLU(alpha=0.2) to the model. At the final dense layer is added with unit of 1 the activation of ‘sigmoid’. The summary() is used to get the information about the model. This discriminator is used for validating the images.

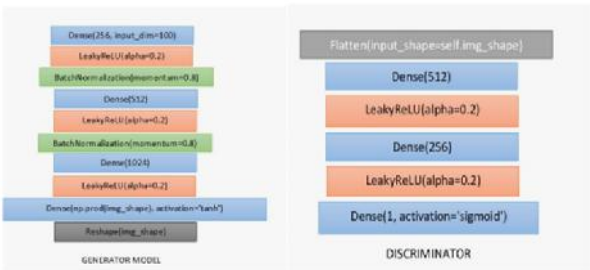

Fig.3. Generator and Discriminator Model

The discriminator model is trained first to distingue real vs fake data. The Generator is trained to create fake images to get better than discriminator. The discriminator validates the data i.e., real or fake and the discriminator loss on fake and real data is calculated in the training process. The final discriminator loss is calculated by taking average of the two losses by discriminator. Similarly, generator loss is also calculated. This training process continues for 3000 epochs to get the best trained result. The weight file is generated at the result of epochs and it is saved and used for image enhancement.

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Fig.4. GAN Architecture

The images form the data set are processed with the EDSR - Enhanced Deep Residual Network, which is trained using GAN model. This EDSR model provides the best in result image enhancement. Here the EDSR model is used with scaling factor 4 to increase the pixel of image up to 4 times of it.

C. Image Data Augmentation

The performance of deep learning neural networks often improves with the amount of data available. Data augmentation artificially create new training data from existing training data. This is done by applying domain-specific techniques to examples from the training data that create new and different training examples.

Image data augmentation involves creating transformed versions of images in the training dataset that belong to the same class as the original image.OpenCV is a great tool for image processing and performing computer vision tasks.

The images in the dataset are loaded from the drive to OpenCV and the image is resized maintaining the aspect ratio of the images. The shape of an image is accessed by “img.shape” . It returns a tuple of the number of rows, columns, and channels. Were,

- Height represents the number of pixel rows in the image or the number of pixels in each column of the image array.
- Width represents the number of pixel columns in the image or the number of pixels in each row of the image array.
- Number of Channels represents the number of components used to represent each pixel

For every 8° angle from 0° to 360° the image is flipped Taking (columns/2, row/2) as center and Scale as 1. The function calculates the following matrix (an affine matrix of 2D rotation):

$$\begin{bmatrix} \alpha & \beta & (1-\alpha)\cdot \texttt{center.x} - \beta\cdot \texttt{center.y} \\ -\beta & \alpha & \beta\cdot \texttt{center.x} + (1-\alpha)\cdot \texttt{center.y} \end{bmatrix}$$

$$\alpha = \texttt{scale} \cdot \cos \texttt{angle},$$
$$\beta = \texttt{scale} \cdot \sin \texttt{angle}$$

The transformation maps the rotation center to itself. If this is not the target, adjust the shift. This returns a 2×3 Rotation Matrix M which is passed as input. OpenCV function cv::warpAffine to implement simple remapping routines. The function warpAffine transforms the source image using the specified matrix:

$$\texttt{dst}(x,y) = \texttt{src}(\texttt{M}_{11}x + \texttt{M}_{12}y + \texttt{M}_{13}, \texttt{M}_{21}x + \texttt{M}_{22}y + \texttt{M}_{23})$$

when the flag WARP_INVERSE_MAP is set. Affine Transformation is represented using a 2×3 matrix.

$$A = \begin{bmatrix} a_{00} & a_{01} \\ a_{10} & a_{11} \end{bmatrix}_{2\times 2} \quad B = \begin{bmatrix} b_{00} \\ b_{10} \end{bmatrix}_{2\times 1}$$

$$M = [A \quad B] = \begin{bmatrix} a_{00} & a_{01} & b_{00} \\ a_{10} & a_{11} & b_{10} \end{bmatrix}_{2\times 3}$$

Considering that we want to transform a 2D vector $X = \begin{bmatrix} x \\ y \end{bmatrix}$ by using A and B, we can do the same with:

$T = A \cdot \begin{bmatrix} x \\ y \end{bmatrix} + B$ or $T = M \cdot [x, y, 1]^T$

$$T = \begin{bmatrix} a_{00}x + a_{01}y + b_{00} \\ a_{10}x + a_{11}y + b_{10} \end{bmatrix}$$

A transformation that can be expressed in the form of a matrix multiplication (linear transformation) followed by a vector addition (translation). This gives 2×3 transformation matrix. And the data obtained from data Augmentation are stored.

D. Feature Selection

Feature extraction helps to reduce the amount of redundant data from the data set. Features like the x and y coordinate of the abnormality in the image, the radius of abnormality etc.… are obtained. The reduction of the data helps to build the model with less machine’s efforts and also increase the speed of learning and generalization steps in the machine learning process.

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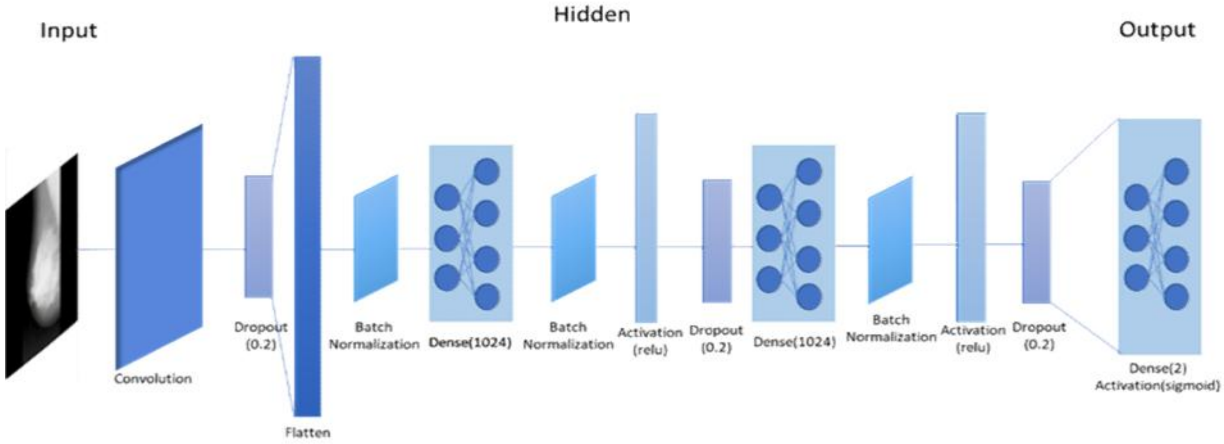

E. Splitting of dataset for Testing,Training and Validation

Initially, the dataset is read from the CSV file. The data entries from the dataset are analyzed on the basis of their features before they were used for further step. Then, we split the dataset into three portions: training set (70%), testing set (25%) and validation set (30% of the training

dataset). The Dataset was split into the mentioned ratio after many tail and error experiments to give better results.

F. Classification

Feature Extracted Image is processed using CNN with LSTM and U-NET for Classification of images. The dataset (5175) which is obtained after data augmentation is split into testing and training. Where 70% (3622) of the images are allocated for training the model and 30% of the data augmented images are allocated for testing on which 70% (1087) of Images are used for validation of the dataset and 30% (466) of the images are used for testing. CNN with LSTM is used for the classification purpose. The Model is trained using CNN-LSTM and the dataset validated with U-NET and the trained model is validated. The Results are classified as Begnin and Maligant.

a) CNN-LSTM with U-Net: The model is build based on several layers as shown in Fig.5. First Inception-ResNet-v2 function is used as base layer for convolution neural network and U-NET with the parameters such as input shape-to specify the shape of image, weights as imagenet, include_top as false. Then sequential function is used to add layer to build the model. Dropout layer is added to the model to reduce the 20 precent neuron connection and the overfitting problem. Flatten

Fig.5. The CNN-LSTM with U-net Layered model of the proposed System

layer is added to the model. BatchNormalization layer is added to the model to increase accuracy. Dense layer is used with unit of 1024, kernel_initilizer as he_uniform to uniformly initialize weights. Again, the BatchNormalization layer is added to the model. Activation relu(rectifier linear unit) layer is added to the model to select the value of 0-1. Again, Dropout layer is added to reduce the redundancy of neuron by 20 percent. Then Dense, BatchNormalization, Activation layer, Dropout layer is continued in the model. The hidden layers are used to build model to improve accuracy. Output layer is added to the model with Dense layer with 2units and activation as sigmoid, sigmoid is used for binary classification of results.

CNN-LSTM: A Convolutional Neural Network, also known as CNN [9] or ConvNet, is a class of neural networks that specializes in processing data that has a grid-like topology, such as an image. Convolutional neural network is one of the

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main categories to do images recognition, images classifications. The CNN Long Short-Term Memory Network or CNN LSTM for short is an LSTM architecture specifically designed for sequence prediction problems with spatial inputs, like images or videos. CNN LSTM architecture (Fig.6) involves using Convolutional Neural Network (CNN) layers for feature extraction on input data combined with LSTMs to support sequence prediction. It is helpful to think of this architecture as defining two sub-models: the CNN Model for feature extraction and the LSTM Model for interpreting the features across time steps [7].

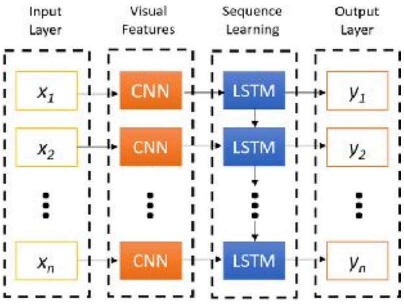

Fig.6. CNN-LSTM model

U-net:

The u-net is convolutional network architecture for fast and precise segmentation of images. It can localize and distinguish borders is by doing classification on every pixel, so the input and output share the same size.

Its architecture can be broadly thought of as an encoder network followed by a decoder network. Unlike classification where the end result of the deep network is the only important thing, semantic segmentation not only requires discrimination at pixel level but also a mechanism to project the discriminative features learnt at different stages of the encoder onto the pixel space.

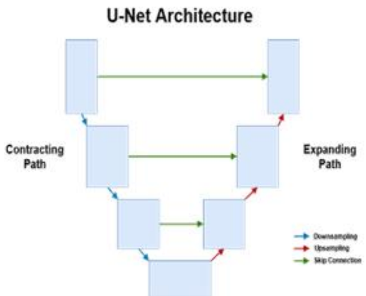

Fig.7. U-net Architecture

V. Results And Evaluation

In this section, the analysis of result and comparison of results is covered. The input data set is mammogram images and they are processed with GAN model to get an enhanced image of input data. The GAN model images are evaluated with parameters like PSNR and MSE Fig.11. The GAN enhanced image is compared with the original image in the values of sharpness Fig.12 and BRISQUE score Fig.13. The images are given to hybrid model and CNN models to classify the image whether it is benign or malignant and both the model's results are compared. Along with this comparison we have compared our model architecture with the same model of reducing number of layers. Comparatively the number of layers in the model alters the accuracy of the model. To analyse the results, we have considered three different train test ratio 70:30, 60:40, and 80:20. All the three ratio results in different classification accuracy. The following formulas were used for result calculation.

True Positive (TP) -The predicted value matches the actual value. The actual value was positive and the model predicted a positive value

True Negative (TN) - The predicted value matches the actual value. The actual value was negative and the model predicted a negative value

False Positive (FP) - The predicted value was falsely predicted. The actual value was negative but the model predicted a positive value

False Negative (FN) - The predicted value was falsely predicted. The actual value was positive but the model predicted a negative value.

Accuracy (ACC) is calculated as the number of all correct predictions divided by the total number of the dataset.

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- $$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Precision explains how many correctly predicted values came out to be positive actually. Or simply it gives the number of correct outputs given by the model out of all the correctly predicted positive values by the model.

It determines whether a model is reliable or not. It is useful for the conditions where false positive is a higher concern as compared to a false negative.

- Precision: TP/(TP+FP)

Recall describes how many of the actual positive values to be predicted correctly out of the model. It is useful when false-negative dominates false positives.

- Recall: TP/(TP+FN)

F-score is a harmonic mean of Precision and Recall, For the condition when two models have low precision and high recall or vice versa, it becomes hard to compare those models, therefore to solve this issue we can deploy F-score.

- F-measure= (2*Recall*precision)/ (Recall + Precision)

The classification report is calculated for the proposed model, CNN model, proposed model with reduced layers. Based on the Accuracy score, F1 score Precision score, Recall score, ROC AUC score and Cohen Kappa score.

Classification matrix Report and Score of the Hybrid Model

Accuracy Score for Hybrid Model: 0.8673535093367676
F1 Score for Hybrid Model: 0.8665963337948059
Precision Score for CNN AND LSTM Model: 0.8660264735264736
Recall Score for CNN AND LSTM Model: 0.8674581285728613
ROC AUC Score: 0.9263
Cohen Kappa Score: 1.0

Classification Report:

	precision	recall	f1-score	support
B	0.89	0.87	0.88	845
M	0.84	0.87	0.86	708
accuracy			0.87	1553
macro avg	0.87	0.87	0.87	1553
weighted avg	0.87	0.87	0.87	1553

Fig.8.Results obtained in Hybrid Model Proposed

Classification matrix Report and Score of the Hybrid Model with less layers

Accuracy Score for Hybrid Model with less layers:
0.708950418544752
F1 Score for Model: 0.7017684286374637
Precision Score for Model: 0.7094902965128856
Recall Score for Model: 0.700713736502524
ROC AUC Score: 0.7693
Cohen Kappa Score: 0.0

Classification Report:

	precision	recall	f1-score	support
B	0.71	0.79	0.75	845
M	0.71	0.61	0.66	708
accuracy			0.71	1553
macro avg	0.71	0.70	0.70	1553
weighted avg	0.71	0.71	0.71	1553

Fig.9. Results obtained in Hybrid Model with 3 layers

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Classification matrix Report and Score of the Hybrid Model with less layers

```
Accuracy Score for CNN Model: 0.5827430779137154
F1 Score for CNN Model: 0.5791750301083902
Precision Score for CNN Model: 0.5792406118493074
Recall Score for CNN Model: 0.5791269682078026
ROC AUC Score: 0.5898
Cohen Kappa Score: 0.0
         Classification Report:
                 precision    recall  f1-score   support

            B       0.62      0.62      0.62       845
            M       0.54      0.54      0.54       708

     accuracy                           0.58      1553
    macro avg       0.58      0.58      0.58      1553
 weighted avg       0.58      0.58      0.58      1553
```

Fig.10. Results obtained in Hybrid Model with 2 Layers

a) GAN Evaluation

PSNR and MSE

The PSNR block computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is used as a quality measurement between the original and a compressed image. The higher the PSNR, the better the quality of the compressed, or reconstructed image.

$$MSE = \frac{\sum_{M,N} [I_1(m,n) - I_2(m,n)]^2}{M * N}$$

The mean-square error (MSE) and the peak signal-to-noise ratio (PSNR) are used to compare image compression quality. The MSE represents the cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error. The lower the value of MSE, the lower the error.

Where, M and N are the number of rows and columns in the input images. Where, R is the maximum fluctuation in the input image data type.

$$PSNR = 10 \log_{10}\left(\frac{R^2}{MSE}\right)$$

The PSNR and MSE values are calculate between the original image and enhanced image. The results are represented in Bar graph.

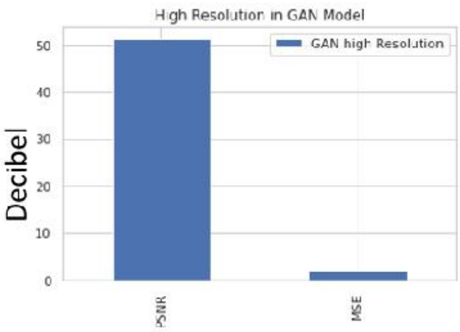

Fig.11. PSNR MSE value for the image enhanced using GAN

SHARPNESS Comparison

sharpness is a combination of resolution and acutance. Acutance is an objective measure of the physical characteristics that underlie the subjective impression of sharpness in an image. Acutance and Subjective Quality Factor (SQF) are measures of perceived print or display sharpness. acutance is determined by imaging a sharp "knife-edge",

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producing an S-shaped distribution over a width W between maximum density D1 and minimum density D2 – steeper transitions yield higher acutance.
Summing the slope Gn of the curve at N points within W gives the acutance value A,

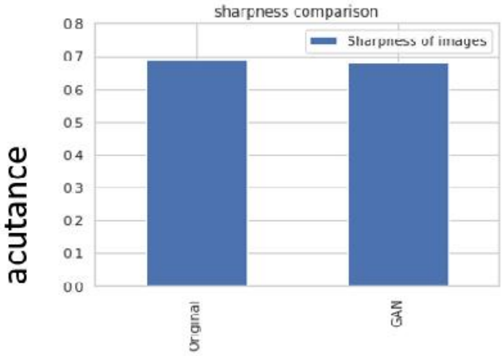

Fig.12 Sharpness comparison

BRISQUE

Brisque predicts the BRISQUE score by using a support vector regression (SVR) model trained on an image database with corresponding differential mean opinion score (DMOS) values. The database contains images with known distortion such as compression artifacts, blurring, and noise, and it contains pristine versions of the distorted images. The image to be scored must have at least one of the distortions for which the model was trained. Score = brisque(A) calculates the no-reference image quality score for image A using the Blind/Reference less Image Spatial Quality Evaluator (BRISQUE). brisque compare A to a default model computed from images of natural scenes with similar distortions. A smaller score indicates better perceptual quality.

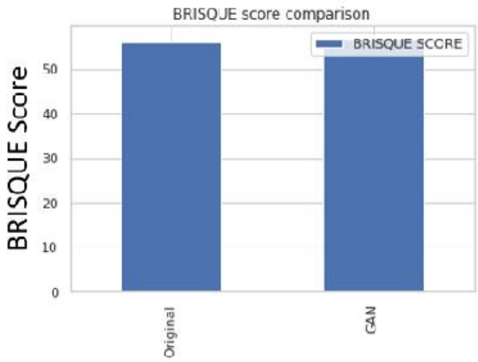

Fig. 5

Fig.13. BRISQE score. This above shown graph are the results of GAN model

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b) Results of Evaluating Classification Model

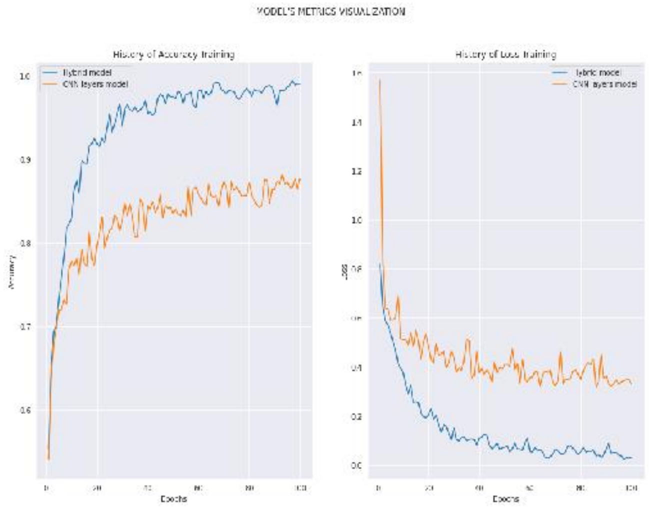

Fig.14. Comparing Accuracy and Loss of Training between proposed model and CNN

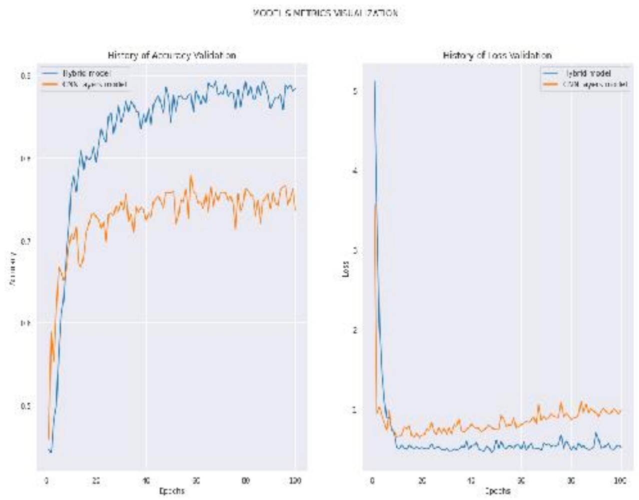

Fig.15. Comparing Accuracy and Loss of Validation between proposed model and CNN.

VI. CONCLUSION

In this work we proposed a Hybrid Deep Learning Model which classifies breast cancer image with better accuracy. The GAN method used here is for the image enhancement purpose. The dataset which we have chosen is from the Mammographic Image Analysis Society (MIAS) dataset mammography images. Mammography has been proposed as an early detection screening method. The Segmentation and classification approach is performed on MIAS Breast cancer images. GAN Model is used for Enhancement of the Mammograms and Feature Extraction. The hybrid model which we proposed here is CNN-LSTN with U-net Model. which can minimize errors and led to an increased in accuracy of breast cancer mammogram classification. Our model gives an accuracy of around 90% which is comparing good with another existing CNN model. We have compared the results of classification with the proposed model and the traditional CNN model and the results are higher in proposed model.

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REFERENCES

[1] Pramit Brata Chanda, Subir Kumar Sarkar, "Detection And Classification Technique Of Breast Cancer Using Multi Kernal SVM Classifier Approach", IEEE Applied Signal Processing Conference, Journal Vol 7, pp 320-325, 2018

[2] Rui Man, Ping Yang, And Bowen Xu, "Classification of Breast Cancer Histopathological Images Using Discriminative Patches Screened by Generative Adversarial Networks", IEEE ACCESS, Journal Vol 8 , pp 155362 -155377 , 2018

[3] Liang Gonog and Yimin Zhou, "A Review: Generative Adversarial Networks",14th IEEE Conference on Industrial Electronics and Applications (ICIEA) , pp 505-510, 2019

[4] Sanket Agrawal, Rucha Rangnekar, Divye Gala, Sheryl Paul and Dr. Dhananjay Kalbande, "Detection of Breast Cancer from Mammograms using a Hybrid Approach of Deep Learning and Linear Classification", IEEE Xplore, 2019

[5] Zhiqiong Wang, Mo Li, Huaxia Wang, Hanyu Jiang, Yudong Yao, (Fellow, Ieee), Hao Zhang, And Junchang Xin, "Breast Cancer Detection Using Extreme Learning Machine Based on Feature Fusion With CNN Deep Features"IEEE Access, Journal Vol 7, pp 105146 – 105158, August 14, 2019

[6] Roslidar Roslidar, Aulia Rahman, Rusdha Muharar, Muhammad Rizky Syahputra, Fitri Arnia, Maimun Syukri, Biswajeet Pradhan and Khairul Munadi, "A Review on Recent Progress in Thermal Imaging and Deep Learning Approaches for Breast Cancer Detection", IEEE Access Journal, Vol.8, pp 116176 -116194, July 2020

[7] Yuliana Jiménez-Gaona, María José Rodríguez-Álvarez and Vasudevan Lakshminarayanan, "Deep-Learning-Based Computer-Aided Systems for Breast Cancer Imaging: A Critical Review", Applied Sciences, pp 1-28, 23 November 2020,

[8] Md. Zabirul Islam, Md. Milon Islam *, Amanullah Asraf "A combined deep CNN-LSTM network for the detection of novel coronavirus (COVID-19) using X-ray images", Elsevier Ltd, pp 1-11, August 2020

[9] Abhijith Reddy Beeravolu, Sami Azam, Mirjam Jonkman, Bharanidharan Shanmugam, Krishnan Kannoorpatti and Adnan Anwar, "Preprocessing of Breast Cancer Images to Create Datasets for Deep-CNN", IEEE Access, Vol.9, pp 33438 - 33463 ,2021

[10] Jingyao Li, Lianglun Cheng, Tingjian Xia, Haomin Ni, And Jiao Li, "Multi-Scale Fusion U-Net for the Segmentation of Breast Lesions" IEEE ACCESS, Journal Vol 9, pp 137125-137139, 2021

[11] Akhil Kumar Das, Saroj Kr. Biswas, Arijit Bhattacharya, And Ekram Alam, "Introduction to Breast Cancer and Awareness" IEEE, 7th International Conference on Advanced Computing and Communication Systems, pp 227-232, 2021