FOREX Publication
Open Access | Rapid and quality publishing

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 12, Issue 1 | Pages 300-307 | e-ISSN: 2347-470X

A Novel Transfer Learning Approach to Improve Breast Cancer Diagnosing on Screening Mammography

Dr. G N Keshava Murthy[1], Dr. Chaitra H V[2], Dr. Vidya E V[3], Dr. Manjula B M[4], and Dr. Chetana Srinivas[5]

[1]Assistant Professor, Department of EIE, Siddaganga Institute of Technology, Tumkur, India.
[2]Associate Professor, Department of ISE, BGS College of Engineering and Technology Bengaluru, India.
[3]Associate Professor, Department of CSE, East West Institute of Technology, Bengaluru, India.
[4]Professor, Department of ECE, Nitte Meenakshi Institute of Technology, Bengaluru, India.
[5]Associate Professor, Department of CSE (AI &ML), PES University, Bengaluru, India

***Correspondence:** chetanasrinivas2008@gmail / achyuth001@gmail.com

ABSTRACT- Segmentation is a technique for separating an image into discrete areas in order to separate objects of interest from their surroundings. In image analysis, segmentation—which encompasses detection, feature extraction, classification, and treatment—is crucial. In order to plan treatments, segmentation aids doctors in measuring the amount of tissue in the breast. Categorizing the input data into two groups that are mutually exclusive is the aim of a binary classification problem. In this case, the training data is labeled in a binary format based on the problem being solved. Identifying breast lumps accurately in mammography pictures is essential for the purpose of prenatal testing for breast cancer. The proposed TLA (Transfer Learning Approach) based CNN (Convolution Neural Network) –TLA based CNN aims to offer binary classification for rapid and precise breast cancer diagnosis (benign and malignant). In order to predict the sub-type of cancer, this exploration as used Deep Learning techniques on the Histogram of Oriented Gradient (HOG) - Feature extraction technique that creates a local histogram of the image to extract features from each place in the image with CNN classifier. This research work employs two well-known pre-trained models, ResNet-50 and VGG16, to extract characteristics from mammography images. The high-level features from the Mammogram dataset are extracted using a transfer learning model based on Visual Geometry Group (VGG) with 16-layer and Residual Neural Network with 50-layers deep model architecture (ResNet-50). The proposed model TLA based CNN has achieved 96.49% and 95.48% accuracy as compared to ResNet50 and VGG16 in the breast cancer classification and segmentation.

Keywords: Deep learning, CNN, digital Mammogram images, image segmentation, Resnet50, VGG16.

ARTICLE INFORMATION

Author(s): Dr. G N Keshava Murthy, Dr. Chaitra H V, Dr. Vidya E V, Dr. Manjula B M, and Dr. Chetana Srinivas;

Received: 24/11/23; **Accepted**: 01/02/24; **Published**: 30/03/24;
E- ISSN: 2347-470X;
Paper Id: IJEER231027;
Citation: 10.37391/IJEER.120141
Webpage-link:
https://ijeer.forexjournal.co.in/archive/volume-12/ijeer-120141.html

crossref member
CROSSREF.ORG
THE CITATION LINKING BACKBONE

Publisher's Note: FOREX Publication stays neutral with regard to jurisdictional claims in Published maps and institutional affiliations.

1. INTRODUCTION

The most common type of cancer in women is breast cancer, which claims the lives of an estimated 40,000 women each year worldwide, continues to be one of the most serious public health challenges. In order to prevent this disease's repercussions as it progresses and lower its morbidity rates in women, early detection is essential. Numerous approaches are used in the clinical diagnosis of breast cancer. Clinical screening is the first method, and it is carried out using radiological pictures such as Magnetic Resonance Imaging (MRI), Mammography, and others [3]. Overuse of mammograms for breast cancer screening has been studied for a long time, which has strongly advocated the development of other medical imaging techniques, such as tumor detection, localization, segmentation and classification. In order to identify the type of tumor in its early stage, radiologists must quickly study and evaluate a large amount of data produced by mammography images; in contrast, multistage procedures typically require more time. It can rank tumor types without passing through numerous phases, which could delay therapy. Since mammography is the most sensitive method now available for identifying nonpalpable breast abnormalities, screening mammography has become a standard part of women's health maintenance. In image processing, segmentation is the process of dividing an image into several sections in order to identify the masses in mammograms and extract the ROI from the picture [28, 29] and [30]. Furthermore, anomalies are simple to find [31, 32]. Pectoral muscles, however, can interfere with identification; for this reason, artifacts and pectoral muscles must to be eliminated before to segmentation.

Determining and segmenting the suspicious area of the tumor is also a highly difficult and time-consuming task. Malignant, Benign, and Normal are the three main categories used for categorization [9]. In various fields, including agriculture, medicine, and forensics, image segmentation technology was extensively employed in pattern detection and picture categorization. In Image processing technique one of the main phases is the segmentation. Segmentation technique is mainly useful to divide an image into various significant regions with the focus of segregating the regions of interest from the background [10]. Tasks like segmentation and classification are achieved based on color and texture features of mammogram images [11]. In the last few years, numerous academic studies have been conducted on breast mass segmentation tasks. For example, a threshold-based, a region- based, a contour-based, and a deep learning-based segmentation method. Making ensuring the contour evolution is not impeded by non-breast edges is difficult when using contour-based methods [4]. Both conventional techniques and pixel classification techniques based on machine learning were examined for region-based segmentation [15]. These techniques typically require additional manual involvement or a parameter selection process, which could result in variances between and between observers. Due to its clarity and simplicity, the thresholding technique was frequently utilized in investigations. One of these methods was Otsu method. This technique, which was heavily modified, was based on the grey scale histogram [16]. First of all, it is straightforward and capable of processing grayscale photos immediately. Due to its low sensitivity to dark areas, it can also operate with global threshold settings. Last but not least, Otsu technique does not require prior knowledge of the histogram's structure [5]. The limitations of traditional machine learning methods motivated the development of the deep learning framework, which automates the entire extraction process from beginning to end and learns the photographs' holistic properties from a low to high level in preparation for categorization. Scholars have expressed great concern over CNN- based feature extraction models among DL models for the classification of histopathological breast pictures. Typically, a significant number of images are required for training supervised deep CNN models in order to get rid of overfitting and function well. However, due to the high potential cost of collecting and upkeep, a significant portion of annotated photos are occasionally unavailable. Additionally, previously trained deep neural networks are fine-tuned using CNNs showed increased tolerance to the larger size of the dataset. Deep tuning and shallow tuning are challenging to distinguish from one another, though, as there are no universal standards for doing so; instead, it depends on unique circumstances [6]. Here, Deep tuning involves fine-tuning every layer of the deep convolutional network, whereas shallow tuning just involves the final few levels of the deep network. For extracting the features from the mammographic pictures, two CNN pre-trained models are utilized, ResNet-50 and VGG16, where "Res" stands for a residual network and "VGG" for a Visual Geometry Group with a 16-layer deep model architecture [2]. The purpose of this research is to evaluate pre-trained deep learning VGG16 as a feature extractor for binary and multiclass breast cancer mammographic image classification tasks, once VGG16 has been tuned for these tasks [7]. One Max-Pool layer, one Average Pool layer, and 48 Convolution layers make up the ResNet50 version of the ResNet model. Here, each filter's maximum value is taken during max pooling, and the results are grouped into a new output that is 2 by 2 pixels in size. On the other hand, the average filter size value is the average pooling value that is used. This framework can be used to carry out a variety of computer vision tasks, such as image categorization, object location, and object detection. It can also be used for activities that are not computer vision-related in order to add the benefit of depth and lower the computing cost.

The subsequent paper is structured as follows: We break this down into five sections. *Section II* provides context for our study, *section III* discusses the proposed approach, *section IV* details the experiment and its results, and *section V* provides visual representations of the findings and suggestions for further improvement.

2. RELATED WORK

Significant number of papers have been published with respect to identification of breast cancer in the early stages. Most of these researches have proposed image filtering and machine learning techniques which include myriad features. The functioning and working of these strategies vary greatly depending upon the algorithms used and training methods intended [2].

Deep learning structures widely used early detection of breast cancer diagnostics. One of the most commonly used deep learning model is CNN; recognizes images and objects with the help of CNN. CNN achieves this by segmenting and classifying images and objects. Several segmentation techniques have been used in a number of studies to classify breast cancer images. They include thresholding, edge, region and clustering based approaches, among which thresholding and clustering based techniques are most accepted methodologies for bifurcating images. Thresholding approach has been established in several areas because of its easy accessibility and directness [5].

For example, Otsu is one of the thresholding-based technique which was obtained from gray scale histogram. It was widely applied because of its various characteristics, one of those are that it doesn’t call for foreknowledge of the histogram’s shape. In paper [5], authors have introduced inverse technique (TsTN) to enhance thresholding-based segmentation that helps in dividing natural image patches. This new, enhanced TsTN method produced threshold values quickly and automatically by using the Otsu method. Nevertheless, producing high-quality segmented images required more than just segmenting the natural images using an automatic threshold value. Consequently, to get better segmented images, the threshold value has to be changed frequently. As both k- means and Otsu approaches were unsuccessful in providing high quality pictures of segmented regions in natural surroundings [5]. Then they compared Otsu, K-means and TsTN methods with the help of chromatic image procedures based on the standard of segmented images [5]. They came out with successful and précised results when compared to classic clustering and thresholding techniques. In other works, like [6], authors have presented a diagnostic system based on ResNet-50 for classifying breast abnormalities. Scaling and Contrast-based Data Augmentation (SCDA) was developed as an extension of scaling and Contrast- based Adaptive Histogram Equalization, an improvement to Existing Data for enhancing the proposed model which when trained with augmented training set resulted in ResNet-SCDA-50. This method is applied on mammogram images collected from INbreast and MINI-MIAS. In this work, authors have applied CLAHE algorithm before giving the patches obtained from the initial mammogram images as input which increased the standard of the images greatly [8]. They reported mean of 98.55% specificity and 92.83% sensitivity, resulting in an overall accuracy of 95.74%. In another research [17], authors have made use of VGG with 16-layer deep model architecture in order to bring out high-end properties using BreaKH - histopathological image dataset. VGG16 is one of the most popular deep learning structured established by University of Oxford [1]. And also used different types of models in machine learning in order to control various histopathological images grouping functions involving mainly one or more classes (categories) with eight-class segmentation approach.

The experiment results surpassed the existing long-established machine learning algorithms with high precision. Moreover, in paper [2], the authors have implemented a multinet architecture established on transfer learning conception for classifying various kinds of ductal carcinomas by making use of generally available microscopic mammary gland images. In this work, they have drawn out required nanoscopic attributes with the help of three familiar models which were trained in advance together with DenseNet- 201, NasNetMobile, and VGG16. A strong combination model was developed by providing the obtained features to concatenate layer. The developed model obtained an accuracy of 99% in categorizing 2 groups whereas obtained 98% accuracy in categorizing 4 groups. Significant number of papers have been published with respect to identification of breast cancer in the early stages [2]. Most of these researches have proposed image filtering and machine learning techniques which include myriad features. The functioning and working of these strategies vary greatly depending upon the algorithms used and training methods intended. From the above works, some points can be concluded:

- While classifying the natural images the use of an automated TsTN value was not enough to obtain standard quality segmented images [5].
- In [6], as we know that functioning of diagnosing system depends upon on the detection system. Hence, they need to work on implementing automatic detection system like CAD which makes the existing process complete. And for CAD, they need large datasets to increase the efficiency and performance.
- Analysing histopathological images consumes more time and is quite tiresome. Even for seasoned pathologists, the examination of such images is not only time- and resource-consuming but also extremely difficult, leading to discrepancies amongst and among observers.
- Using separate models is significantly difficult task and ensemble models are preferred for this complex domain.

3. PROPOSED METHODOLOGY

3.1 Deep Learning

CNN is regarded as a leading deep learning approach among all other deep learning approaches. It has been utilized for numerous data science applications, including feature extraction from input training photos and categorization of medical images using a pre-trained CNN model [1]. The key to CNN-based segmentation networks is to learn reliable high-resolution features. CNN, a feed- forward neural network, solves the limitations of fully connected neural networks by being simple to train and generalize as shown in *figure 1* [6].

The main components of CNN are Input layer, Convolution Layer, Pooling Layer, Fully Connected Layer and Output Layer. According with the suggested model, the input layer contains image data. Three- dimensional matrices are used to represent image data. In order to feed the input layer, the picture matrix is flattened into a single column vector. The number of convolutional layers within a network is determined by its specifications. Convolution layer, the output is often forwarded to other convolutional layers. By decreasing the number of links between convolutional layers, the Pooling Layer lightens the computational strain by increasing the resolution or spatial size of the convolved features. Prior to the Softmax layer is the Fully Connected Layer, the number of which changes based on the necessity. For binary and multi-class classification, the Softmax classifier is the best suitable. The label which is one-hot encoded, is present in the output layer [1,6].

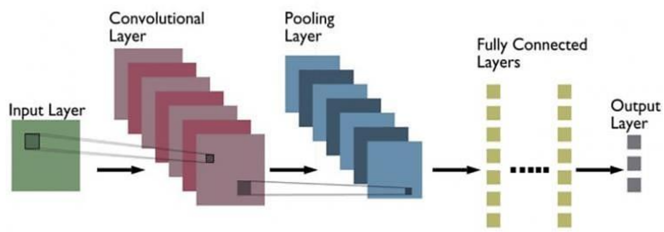

Figure 1 : Model of Convolution Neural Network

4. PROPOSED SEGMENTATION OF LESIONS IN MAMMOGRAM IMAGING

In proposed work, Basic Global thresholding (Adaptive thresholding and Ostu thresholding) as image segmentation techniques is used. Thresholding is a technique that separates items from their backdrop by giving each pixel a value for their intensity, T [12]. By transforming the grayscale image into binary images, the threshold values were then used to separate the interest area from its backdrop. The binary pictures are made up of only black and white pixels, with any remaining pixels that have a grey level that is higher than the threshold values being set to black. With this thresholding method, the parameter T can be set dynamically at the start of the process to meet the needs of a wide range of dataset [18].

The following are the steps of the proposed method for segmenting lesions in breast cancer:

(1) Mammography images segment into two groups with a hybrid threshold approach comprised of Otsu's and Adaptive methods with four thresholds.

(2) Conversion from RGB to grayscale of the acquired images.

International Journal of
Electrical and Electronics Research (IJEER)
Open Access | Rapid and quality publishing
Research Article | Volume 12, Issue 1 | Pages 300-307 | e-ISSN: 2347-470X

(3) A set of pixels with intensity values between 120 and 160 was picked (ROIs), In order to correctly separate the areas of interest.
(4) Scan the top one-fourth of the image, which contains the muscle area, and convert it to zeros; this is necessary since the pectoral muscle shares characteristics with the tumor area and must then be removed.

(5) The tumour region is represented by the object with the biggest area after calculating the sizes of the remaining objects in the image.

(6) Using an expert-determined reference image to evaluate the created tumor region.

Adaptive thresholding is used, much like global thresholding, to isolate the crucial foreground and background elements from the photographs. Because the threshold value in adaptive thresholding is measured for a smaller region, it varies depending on the region. To convert the image's characteristics into ROIs, the method used an adaptive thresholding methodology based on the maximum entropy concept, developed to identify breast cancer in its early stages. Enforcing Ostu thresholding has as its main goal the processing of the image histogram and the segmentation of objects by minimizing variance on each class. This unsupervised and non- parametric technique method seeks the optimal threshold value with the lowest weighted variance between lesion and normal tissue pixels. It is an automatic threshold selection technique that divides the image into classes using the best threshold values by optimizing the between-class variance. Researchers may now extract objects of interest from the background using the Otsu approach, which was added to automatically generate threshold values. To address this spot difficulty, a method based on Otsu's binarization was created that constrained the search space of the ideal segmentation threshold for foreground object splitting [13]. The grayscale intensity values of an image's pixels are used to divide it into two classes: background and foreground. Moreover, Otsu's approach finds the ideal threshold value between two regions with the greatest inter-class variance using the grayscale histogram of the picture. The implementation of Ostu thresholding shown in *figure 2.a* and Adaptive thresholding indicated in *figure 2.b* of *figure 2*.

Figure 2.a Ostu thresholding

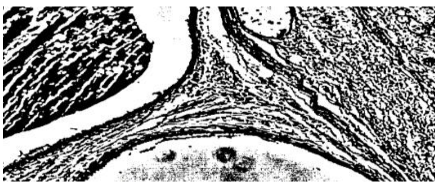

Figure 2.b Adaptive thresholding
Figure 2: Segmentation methods of Breast lesion

4.1 ResNet 50

A modernized version of CNN called Residual Neural Network (ResNet) uses the skip connection method to train deep neural networks with more than 150 layers [1]. ResNet connects the residual blocks in a series as well as through skip.

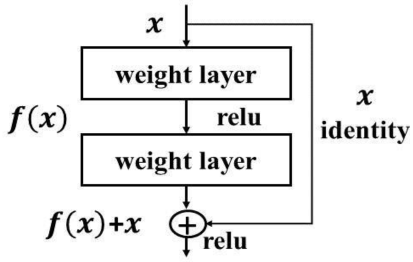

Figure 3. Block diagram of Residual Building Network

connections between neighboring residual blocks [6]. A convolutional network called Resnet-50 takes advantage of residual learning. Problems with CNN's optimization and overfitting cause training error to grow. Skip connections are frequently employed within residual blocks to improve overall accuracy. To prevents layers from training, their primary purpose is to solve the vanishing gradient problem. If the basic block's input size and output size match, just perform the identity mapping; otherwise, the size is adjusted using padding or max-pooling. CNNs can perform better in a variety of computer vision applications by lowering spatial dimensions, maintaining key characteristics, and utilizing basic CNN strategies like pooling and padding. Remaining modules allow Residual Networks to train such deep networks. Training is completed more quickly because the shortcut connections are constantly active and the gradients to back propagate with relative ease. For more complicated features, a more sophisticated and deeper network is required; ResNet has less expensive and challenging design issues. By applying the right optimization function and a normalized network initialization as extremely deep neural networks are trained, the ResNet reduces these issues. The only difference is a skip link running parallel to standard convolutional layers. This shortcut also enables backpropagation, which accelerates optimization. It was created to address the problem of vanishing gradients in deep networks, which was a major impediment to the development of deep neural networks. The ResNet architecture allows the network to learn numerous layers of features without becoming stuck in local minima, which is a typical problem with deep networks. The Figure 3 represents the block diagram of residual building network.

Optimizers are techniques or approaches that adjust the characteristics of the neural network, such as weights and learning rate, to reduce losses such as

•Gradient Descent to adopt backpropagation in neural networks.

•Stochastic Gradient Descent used more frequently to update hyperparameters of the proposed model.

•Mini-Batch Gradient Descent is an improvised approach which updates model's hyperparameters in each batch

Research Article | Volume 12, Issue 1 | Pages 300-307 | e-ISSN: 2347-470X

4.2 VGG16

Oxford University introduced one of the most popular deep learning architectures, VGG16. *Figure 4* depicts the main components of VGG16 architecture. Comprised of 16 weight layers, 13 convolutional layers (Conv.), and 3 fully connected (FC) layers, the network has a total of 41 layers.

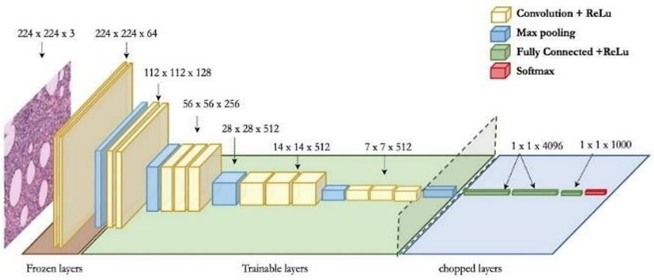

Figure 4: VGG16 architecture

It chooses the optimizer function and initializes the network by considering the hyper-parameters adopted. On each and every Conv Layer with stride 1, VGG16 employs a small 3x3 kernel (filter). Layers that will extract the most dominant features from the adjusted feature map are always followed by max pooling layers [1, 2]. Convolution is just the application of a filter to an input, which results in activation. When the same filter is applied to an input repeatedly, it produces a map of activations known as a feature map, which indicates the positions and strength of a recognized feature in an input, such as an image. The three-channel, 224x224 images serve as input for VGG16. Overall, the convolution layers, ReLU activation function is used. To produce predictions, a single neuron is present in the output layer. It generates a probability output in the 0–1 range using the sigmoid activation function, which is readily and automatically translated into distinct class values. The soft-max layer assigns the decimal probability on the input image, serves as the output layer [1]. It is used in the CNN's output layer and added up upto 1.0, to make final prediction in the multiclass problem. The soft-max layer determines the probability on the input image, serves as the output layer [1]. Binary cross-entropy loss function makes up the final output layer which is mathematically shown in *equation (1)*. Additionally, the first block was frozen during training using VGG16, and the remaining four blocks were used (containing two convolve layers and one max-pooling layer). Once more, in the research used a 256-node dense layer as a single unit and the identical binary cross- entropy loss function. Likewise, trained all the blocks and a single dense layer with 128 nodes for the fully-trained VGG16 [14]. VGG16's last layer is denoted by *equation (1)*, is also a binary cross-entropy loss function.

$$\text{Binary Cross Entropy} = -\frac{1}{m}\sum_{i}^{m}\left(y_i^* \log\left(p(y_i)\right) + (1-y_i) * \log\left(1-p(y_i)\right)\right) \quad (1)$$

5. EXPERIMENTS AND RESULTS

The mammography images used in this article were from kaggle.com. The Digital Database for Screening Mammography (DDSM) is a collection of digitalized mammograms, along with relevant data. There are 154 benign photos, 257 malignant images, in the collection. The breast dataset is split with 80% for training and 20% for testing at random. The images are being resized for the enhancement although the original size of the image is 700X460 pixel and after the processing techniques the image usually is resized. The image for training and testing is subjected to the pre-processing methods.

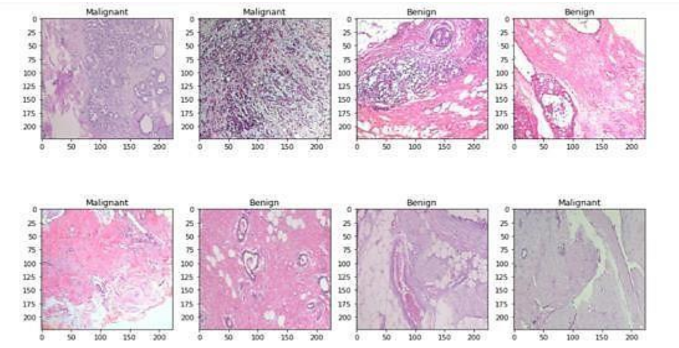

Figure 5: Classified and labelled Benign and Malignant tumour of ResNet50

Figure 5 and *fig. 6* shows the classified and labelled Benign and Malignant tumour in breast lesion detection from ResNet50 and VGG16.

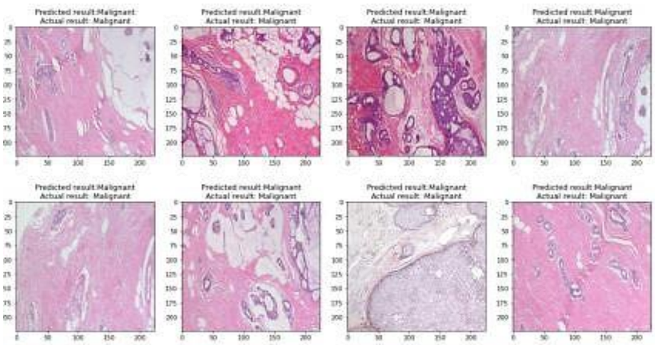
Figure 6. Classified and labelled Benign andMalignant tumour of VGG16

The model performance is quantified by AUC-ROC outcome and classification accuracy. The Area Under the Curve (AUC) is the most often used statistic for estimating classification performance. *Figure 7* depicts the ROC curve, which is generated by plotting the True Positive Rate (TPR) versus the False Positive Rate (FPR).

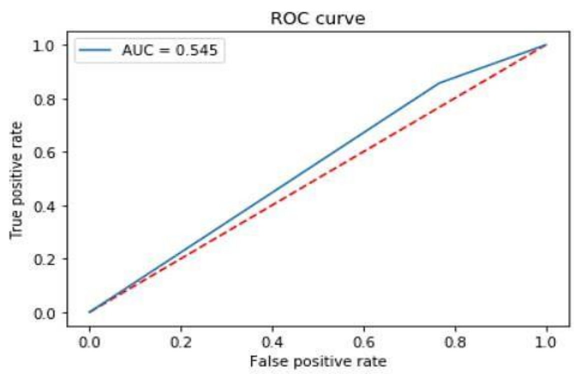

Figure 7. ROC Curve

FOREX Publication
Open Access | Rapid and quality publishing

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 12, Issue 1 | Pages 300-307 | e-ISSN: 2347-470X

Receiver Operating Characteristic (ROC) is the graphical representation of a binary classifier system's diagnostic capability when its inequity threshold varies and also shows performance of the classification models of all classification thresholds. The ROC is determined by dividing the current value of a stock or index by its value in a prior time interval. To convert the value to a percentage, subtract one and multiply by 100. ResNet uses the residual block to address the decomposition and gradient disappearance problems prevalent in existing CNN. The residual block is not dependent on the depth of the network, but it does improve system performance. Unlike, VGG architecture is also an object recognition model hence using all these models is appreciative. As par with the Implementation of VGG 16 particularly; both networks have achieved state-of-the-art results in the ImageNet classification task. In *equation (2)*, we can see what kind of function residuals have:

$$x=F\ (x,\ W)\ +y \qquad (2)$$

Where y is the residual block's input; W stands for the block's weight, and x implies the output. Networks with larger number (even with the count of thousands) training layers do not lead to a rise in the percentage of errors encountered during training. ResNet50's identity mapping functionality is useful for dealing with the disappearing gradient issue Here, we dissect and identify a subset of the mammography dataset that has been somewhat modified to serve as a training and testing ground for our model alongside that of other definitive networks. Since the primary mammogram consists of noises which are not required due to its prospective sampling, the noise artifacts are removed to enhance the time efficiency and accuracy.

The concept on which ResNet50 and VGG16 work is to construct deeper networks contrast to other simple networks and along with finding a concurrent number of layers to invalidate the vanishing gradient problem. The Figure explains the type of layer in output model architecture with output shape and parameter, which results in layers having number of trainable parameter and non-trainable parameters Figure 8 shows ResNet-50 and VGG16 output Model architecture with types of layers in the network. The proposed model has obtained an accuracy of 96.49% and 95.48%, with validation accuracy of 100% and loss rate of 13.17% and 12.84% with validation loss of 0.15% and 0.16% with ResNet and VGG respectively.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 densenet201 (Functional)    (None, 7, 7, 1920)        18321984

 global_average_pooling2d (G  (None, 1920)             0
 lobalAveragePooling2D)

 dropout (Dropout)           (None, 1920)              0

 batch_normalization (BatchN  (None, 1920)             7680
 ormalization)

 dense (Dense)               (None, 2)                 3842

=================================================================
Total params: 18,333,506
Trainable params: 18,100,610
Non-trainable params: 232,896
```

Figure 8. ResNet-50 and VGG16 output Model architecture with types of layers in the network

Accuracy is the factor we concentrate about for the proposed system to be maximized and Loss is addition of the faults developed for every instance in sets used for training or approval. Loss can be caused due to reasons like having the blur datasets or any processing errors.

Hence by considering experiments and study which always look after for an improvement and minimize the loss obtained. To reduce the model's error as much as possible, neural networks employ optimal algorithmic model such as stochastic gradient descent. To calculate this inaccuracy, we employ a tool called a Loss Function. The proposed method is also analyzed with other extant methods and the results are tabulated in *table I*.

The proposed model demonstrated the best results in accuracy in the identification of the breast cancer from the input image either its benign or malignant through different networks (ResNet50 and VGG). We have obtained more than 95% of accuracy in all the kinds of network by correctly implementing the pre-trained models. *Figure 9* illustrates the expected and the actual outcomes of the input image dataset.

Table I: Performance Evaluation metrics ofResNet50 and VGG

Classifier Name	Ts Acc (%)	Ts Loss (%)	Val Acc (%)	Val loss (%)	Tr Acc (%)	Tr Loss (%)	Rec all (%)	Pre (%)
ResNet50	96.79	13.1	100	15.	95.2	18.2	82.2	79.4
VGG	95.48	12.8	100	16.	97.8	22.1	94.7	88.5
TLA based CNN Model	97.13	0.81	96.83	11.8	97.79	18.4	97.2	98.3

The proposed model demonstrated the best results in accuracy in the identification of the breast cancer from the input image either its benign or malignant through different networks (ResNet50 and VGG). We have obtained more than 95% of accuracy in all the kinds of network by correctly implementing the pre-trained models. The *figure 9* illustrates the expected and the actual outcomes of the input image dataset.

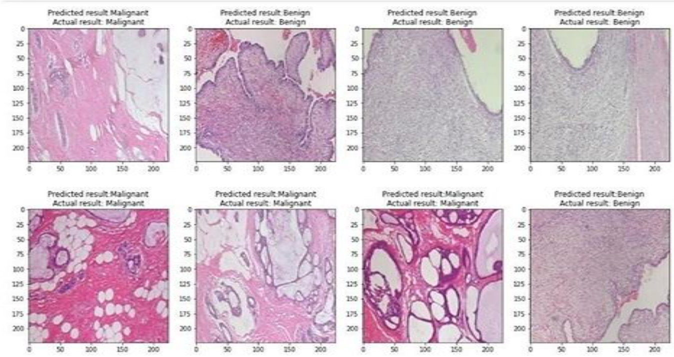

Figure 9. The Predicted and Actual Result of the Breast Lesions

5. CONCLUSION

Segmentation process is an efficient stage in any machine learning based work involving images to be analyzed. In our work, we have used two CNN pre-trained models, namely ResNet-50 and VGG16 for obtaining attributes from mammographic images. VGG16 acts as a feature extractor of categorizing functions of binary and multiclass mammographic images. This process is done after properly tuning up the VGG16 model. On the other hand, ResNet-50 is used for functions like image classification, object detection and object localization. Our developed system using previously mentioned models provided the ResNet-50 giving 96.49% and VGG16 giving 95.48% of accuracy. In future we need to focus on using large dataset in order to increase precision and efficiency of the proposed system. Furthermore, we can investigate and implement using other datasets also as mammogram images aren't always accurate and may show false- negative and false-positive results leading to cause of death.

DATA AVAILABILITY STATEMENT

The research findings are investigated with online publicly accessible available online Kaggle datasets at https://www.kaggle.com/preetviradiya/breast-tumor-dataset supported to do the research work.

REFERENCES

[1] N. A. Prasad and C. D. Guruprakash, "An ephemeral investigation on energy proficiency mechanisms in WSN," 2017 3rd International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT), Tumkur, 2017, pp. 180-185.

[2] S. Chaudhury, N. Achyutha Prasad, S. Chakrabarti, C. A. Kumar and M. A. Elashiri, "The Sentiment Analysis of Human Behavior on Products and Organizations using K-Means Clustering and SVM Classifier," 2022 3rd International Conference on Intelligent Engineering and Management (ICIEM), 2022, pp. 610-615, doi: 10.1109/ICIEM54221.2022.9853128.

[3] Chetana Srinivas, Nandini Prasad K S, Zakariah, M., Alothaibi, Y. A., Shaukat, K., Partibane, B., & Awal, H. (2022). Deep Transfer Learning Approaches in Performance Analysis of Brain Tumor Classification Using MRI Images. Journal of healthcare Engineering 2022, Article ID 3264367, 17 pages.

[4] P. N and C. D. Guruprakash, "A Relay Node Scheme for Energy Redeemable and Network Lifespan Enhancement," 2018 4th International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT), Mangalore, India, 2018, pp. 266-274.

[5] G, M. ., Deshmukh, P. ., N. L., U. K. ., Macedo, V. D. J. ., K B, V. ., N, A. P. ., & Tiwari, A. K. . (2023). Resource Allocation Energy Efficient Algorithm for H-CRAN in 5G. International Journal on Recent and Innovation Trends in Computing and Communication, 11(3s), 118–126. https://doi.org/10.17762/ijritcc.v11i3s.6172.

[6] N. G and G. C. D, "Unsupervised Machine Learning Based Group Head Selection and Data Collection Technique," 2022 6th International Conference on Computing Methodologies and Communication (ICCMC), 2022, pp. 1183-1190, doi: 10.1109/ICCMC53470.2022.9753995

[7] Achyutha Prasad, N., Guruprakash, C.D., 2019. A relay node scheme of energy redeemable and network lifespan enhancement for wireless sensor networks and its analysis with standard channel models. International Journal of Innovative Technology and Exploring Engineering 8, 605–612.

[8] Mohan, B. R. ., M, D. ., Bhuria, V. ., Gadde, S. S. ., M, K. ., & N, A. P. . (2023). Potable Water Identification with Machine Learning: An Exploration of Water Quality Parameters. International Journal on Recent and Innovation Trends in Computing and Communication, 11(3), 178–185. https://doi.org/10.17762/ijritcc.v11i3.6333.

[9] R. V S and Siddaraju, "Defective Motes Uncovering and Retrieval for Optimized Network," 2022 6th International Conference on Computing Methodologies and Communication (ICCMC), 2022, pp. 303-313, doi: 10.1109/ICCMC53470.2022.9754109.

[10] Achyutha Prasad, N., Guruprakash, C.D., 2019. A relay mote wheeze for energy saving and network longevity enhancement in WSN. International Journal of Recent Technology and Engineering 8, 8220–8227. doi:10.35940/ijrte.C6707.098319

[11] Prasad N. Achyutha, Sushovan Chaudhury, Subhas Chandra Bose, Rajnish Kler, Jyoti Surve, Karthikeyan Kaliyaperumal, "User Classification and Stock Market-Based Recommendation Engine Based on Machine Learning and Twitter Analysis", Mathematical Problems in Engineering, vol. 2022, Article ID 4644855, 9 pages, 2022. https://doi.org/10.1155/2022/4644855

[12] Rekha VS, Siddaraju., "An Ephemeral Analysis on Network Lifetime Improvement Techniques for Wireless Sensor Networks", International Journal of Innovative Technology and Exploring Engineering, vol. 8, issue 9, 2278-3075, pp. 810–814, 2019.

[13] Chetana Srinivas, Nandini Prasad K S, Zakariah, M., Alothaibi, Y. A., Shaukat, K., Senthamil Selvan, & Musah Alhasaan. (2022), "Predictive Analysis of various preprocessing techniques in brain tumour detection", Accepted for Publication in Hindawi Journal of Healthcare Engineering Volume 2022, Article ID 7617245.

[14] Rekha, V.S., Siddaraju (2023). Goodness Ratio and Throughput Improvement Using Multi-criteria LEACH Method in Group Sensing Device Network. In: Kumar, A., Senatore, S., Gunjan, V.K. (eds) ICDSMLA 2021. Lecture Notes in Electrical Engineering, vol 947. Springer, Singapore. https://doi.org/10.1007/978-981-19-5936-3_50

[15] Achyutha Prasad, N., Guruprakash, C.D., 2019. A two hop relay battery aware mote scheme for energy redeemable and network lifespan improvement in WSN. International Journal of Engineering and Advanced Technology 9, 4785–4791. doi:10.35940/ijeat.A2204.1091.

[16] N. Szekely, Bela Pataki, "Detecting lesions in a mammogram", 2003.

[17] Achyutha Prasad N., Chaitra H.V., Manjula G., Mohammad Shabaz, Ana Beatriz Martinez-Valencia, Vikhyath K.B., Shrawani Verma, José Luis Arias-Gonzáles, "Delay optimization and energy balancing algorithm for improving network lifetime in fixed wireless sensor networks", Physical Communication, Volume 58, 2023, 102038, ISSN 1874-4907.

[18] P. B.D, A. Prasad N, Dhanraj and M. T N, "Adaptive Voting Mechanism with Artificial Butterfly Algorithm based Feature Selection for IDS in MANET," 2023 IEEE International Conference on Integrated Circuits and Communication Systems (ICICACS), Raichur, India, 2023, pp. 1-7, doi: 10.1109/ICICACS57338.2023.10099861.

[19] P. K. Pareek, A. P. N, C. Srinivas and J. B. N, "Prediction of Rainfall in Karnataka Region using optimised MVC-LSTM Model," 2023 IEEE International Conference on Integrated Circuits and Communication Systems (ICICACS), Raichur, India, 2023, pp. 1-8, doi: 10.1109/ICICACS57338.2023.10100324.

[20] S. Bhattacharyya, H. Rekha, S. Sarkar, N. Achyutha Prasad, B. N. Jagadeesh and S. Verma, "2.4 GHz Operational PSI-Shaped Patch Antenna Design for Multi-Purpose Applications," 2023 2nd International Conference on Smart Technologies and Systems for Next Generation Computing (ICSTSN), Villupuram, India, 2023, pp. 1-6, doi: 10.1109/ICSTSN57873.2023.10151612.

[21] G. . T., R. . V., and U. K. . N. L., "Detecting Security Threats in Wireless Sensor Networks using Hybrid Network of CNNs and Long Short-Term Memory", Int J Intell Syst Appl Eng, vol. 12, no. 1s, pp. 704–722, Sep. 2023

[22] Pooja Chopra, Vijay Suresh Gollamandala, Ahmed Najat Ahmed, S. B. G. Tilak Babu, Chamandeep Kaur, N. Achyutha Prasad, Stephen Jeswinde Nuagah, "Automated Registration of Multiangle SAR Images Using Artificial Intelligence", Mobile Information Systems, vol. 2022, Article ID 4545139, 10 pages, 2022. https://doi.org/10.1155/2022/4545139Tavel, P. 2007 Modeling and Simulation Design. AK Peters Ltd.

[23] Prasad, A. K. ., M, D. K. ., Macedo, V. D. J. ., Mohan, B. R. ., & N, A. P. . (2023). Machine Learning Approach for Prediction of the Online User Intention for a Product Purchase. International Journal on Recent and Innovation Trends in Computing and Communication, 11(1s), 43–51. https://doi.org/10.17762/ijritcc.v11i1s.5992.

[24] Nirmala, G., Guruprakash, C.D. (2023). An Overview of Data Aggregation Techniques with Special Sensing Intelligent Device Selection Approaches. In: Kumar, A., Senatore, S., Gunjan, V.K. (eds) ICDSMLA 2021. Lecture Notes in Electrical Engineering, vol 947. Springer, Singapore. https://doi.org/10.1007/978-981-19-5936-3_58.

[25] G. T and U. N. L, "Routing and Security in Wireless Ad-Hoc Networks: State of the Art and Recent Advances," 2023 IEEE Renewable Energy and Sustainable E-Mobility Conference (RESEM), Bhopal, India, 2023, pp. 1-8, doi: 10.1109/RESEM57584.2023.10236306

[26] Rekha V S and Dr. Siddaraju (2023), A Novel Buffer Packet Delivery Strategy for High Throughput and Better Health (HTBH) Method in Wireless Sensor Networks. IJEER 11(3), 866-876. DOI: 10.37391/ijeer.110334.

[27] Nirmala G and C D Guruprakash (2023), A Novel Modified Energy and Throughput Efficient LOYAL UN-Supervised LEACH Method for

Wireless Sensor Networks. IJEER 11(4), 877-885. DOI: 10.37391/ijeer.110401.

[28] Vikhyath K B and Achyutha Prasad N (2023), Optimal Cluster Head Selection in Wireless Sensor Network via Multi-constraint Basis using Hybrid Optimization Algorithm: NMJSOA. IJEER 11(4), 1087-1096. DOI: 10.37391/ijeer.110428.