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# Attention ResNet Coupled Convolutional Neural Network Model for Breast Cancer Detection using Mammographic Images

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**Abstract:** All over the world, most of the people are affected by breast cancer which results in a high mortality rate. The mortality rate is reduced by early diagnosis, which improves the patients survival rate. The detection of breast cancer at early stage is analyzed by imaging methods as ultrasound and mammographic images. In general, the most common method to detect breast cancer is mammogram analysis, which is a time-consuming process. Several researches diagnosed breast cancer with various analyses, but prior methods need more improvement for better diagnosis. In this, the A2Res-CNN model is utilized for automatically detecting breast cancer with better accuracy. The model trained the extracted features by minimizing the classification loss through the attention mechanism. In this proposed method, the feature extraction is carried out with more efficient A2Res-50. The A2Res-50 enhances the model performance ability with better breast cancer detection. The A2Res-CNN model achieves evaluation metrics of accuracy 96%, sensitivity 97%, and specificity 95%.

***Keywords:*** *Breast cancer detection, Attention module, Mammography images, ResNet50, and Convolutional Neural Network.*

## 1 Introduction

Recent research of World Health Organization (WHO) 2012, presented a report by the International Agency for Research on Cancer (IARC) that undergoes 8.2 million deaths are caused by cancer diagnosed [7] and 6.6% of deaths are caused by cancer-related problems [8][2]. Probably in 2030, the cancer death ratio will increase to 27 million [9] [6]. In most of the other common cancers, women are widely affected by breast cancer, which is the most deadly and is identified by the growth of abnormal cells in the breast tissues. The two classes of tumors are malignant and benign, where the cells that grow locally without any aggregate propagation in breast tissue are named benign, and the abnormal cells that grow in the breast tissue with multiple invasions by affecting the surrounding tissue are defined as malignant cells [6]. The abnormalities that are present in the breast tissues are defined as masses, areas that asymmetry, micro-classification, and distortion. Based on these abnormalities, the most common lesion type of breast tissue is masses. Some of the tissue present in breast cells is also the same as the masses. These masses are very challenging to identify in the breast tissue because it is easily hidden in the overlapped tissue present in the breast. During the detection process, these tissues are wrongly misclassified as masses. This misidentified mass is defined as a false positive, and which undergoes additional examination processes like rescreening which causes patient pain and anxiety [6].

Several imaging techniques are used for detecting the breast cancer such as mammographic technique, magnetic resonance imaging (MRI), and ultrasound techniques [9][6]. In early-stage screening and detection, the cancer cells are analyzed by mammography [1]. While a large number of mammograms are utilized for the breast cancer detection it consumes more time and effort to evaluate every mammogram [10-12]. Due to this, the utility and efficiency of the mammography is reduced. To achieve better accuracy of cancer detection, classification, and segmentation, [13][14][6] the computer-aided diagnosis (CAD) system is utilized to identify the early symptoms of breast cancer that detect the masses from the mammographic images [15][6]. In the CAD system, constant, rapid, and dependable diagnosis is achieved, which consists of pre-processing, feature extraction, and detection the benign and malignant cells [16]. The evaluation of mammography involves lower treatment costs, low efficiency, and computation cost [17]. The traditional machine learning model processed random sampling which excludes some important information and attains maximum over-fitting problem [4]. An ensemble

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classifier computes high computation costs for the acquisition of large chain processes [2].

The research is introduced to detect breast cancer effectively by the A2Res-CNN model. For effective detection, the model includes channel-position attention modules that increase the model performance and reconstruct the images. By this, the proposed A2Res-CNN identifies breast cancer and performs the detection process effectively.

Channel position Attention: In this research, the channel position attention mechanism provides the detection and segmenting process by enhancing the model performance with relevant information on channel and spatial dependencies attained from the input image.

A2Res-CNN: This A2Res-CNN model integrates the benefits of mixed attentional modules like channel and positional modules with the DCNN model for the effective detection of breast tumors with their respective types.

This research paper is regularized as follows; section 2 encompasses on the literary article of prior works along with its challenges. Section 3 describes the detection process of breast cancer with its significance. Section 4 interprets experiment result with its performance and comparative analysis. Finally, section 5 serves as the conclusion of the research.

## 2 Methodology

Jawad Ahmad, et al. [1] implemented a BreastNet-SVM method for classifying and detecting the breast cancer using mammograms. In this Support Vector Machine was utilized for the classification process which was examined under the DDSM dataset. For breast cancer detection in mammograms, the CNN was developed. This neural network detects the abnormalities in breast cancer more accurately. This model provides better accuracy in detecting breast cancer. Thus single dataset was used to identify the benign and malignant tissue which does not employ both training and validation. For the training and validating process additional dataset with distinct optimization was developed. Usman Naseem, et al. [2] utilized an ensemble classifier for automatically detecting breast cancer which was examined under a Wisconsin Breast Cancer Diagnosis and Prognosis database. It generated a feature detection for a complex database in this ensemble classifier. In this ensemble classifier, several classifiers were implemented for detecting the tumor tissues but a single classifier can't classify the feature of the breast cancer. Some of the classifiers required a large chain for the computation process which resulted in increased computation cost. Rosario Lissiet Romero Coripuna, et al. [4] presented a breast conductivity index with quantitative risk factors based on machine learning techniques. These learning techniques were examined by a Mexican patient dataset with 12 attributes. The conductivity index increased the classification accuracy with the reduction of the number of attributes to a minimum range of 3. The electrical conductivity improved the feature accuracy. While the model was processed under random oversampling some important information of the model was excluded and attained maximum over-fitting problem by increasing the learning algorithms. Data acquisition was also evaluated in future studies.

Amin Ul Haq, et al. [3] predicted supervised and unsupervised methods by machine learning algorithm for breast cancer detection. For supervised techniques used Relief algorithm and for unsupervised techniques Autoencoder, and Principal Components analysis algorithm were used. These algorithm techniques were evaluated under WBC, BCD, BCP, and WBCD datasets. The major benefits attained in this machine learning algorithm were easily implemented so the computation cost was reduced also the unsupervised technique does not have any labels to extract the features of the breast cancer cells. To detect the cancer tissue this model needs to enhance the model efficiency for accurate detection. The performance and the feature extraction of the selected algorithm of the machine learning method were reduced. These problems were overcome by introducing deep learning methods to improve the model performance in future directions. Abhishek Das, et al. [5] employed a ensemble learning algorithm based on deep-stacked model for improving the breast cancer classification with better evaluation. This model also includes dual-stage classification to increase the system's performance. The first layer involved a convolutional neural network which undergoes a training process while the second layer included a multi-layer Perceptron (MLP) for validating the process. These were evaluated by the Kaggle public dataset. In image classification, the performance of the model was increased and improved.

### 2.1 Challenges

The significant shortcomings of the prior methods are mentioned as,

The breast conductivity index-based machine learning model was processed under random sampling, where some important information of the model was excluded, and attains maximum over-fitting problem was increased in the learning algorithms. Data acquisition was also evaluated in future studies [4].

To detect the cancer tissue, the supervised and unsupervised learning technique model need to improve the efficacy of the model for accurate detection. The performance and the feature extraction of the selected algorithm of the machine learning method were reduced. These problems were overcome by introduced deep learning methods to improve the model performance in future directions [3].

In the ensemble classifier, several classifiers were implemented for detecting the tumor tissues, where some of the classifiers require large chains for the computation process which results in increased computation cost [2].

The BreastNet-SVM method used a single dataset to identify the benign and malignant tissue, which does not employ both training and validation. For the training and validating process additional dataset with distinct optimization was developed [1].

## 3 Methodology

Breast cancer is obtained by growing an abnormal cell in the breast tissue, where multiple invasions of the breast tissues are classified as a benign and malignant class. In this, benign is non-cancerous cells, whereas malignant is referred to as cancerous cells.

### 3.1 Interdisciplinary Approach

In the field of medical science detecting a malignant cell is a challenging task. Earlier doctors used to detect manually malignant node on the basis of mammogram, MRI, Ultrasound, biopsy and few more techniques**.** the existing methods of breast cancer detection have some limitations like efficiency, accuracy, and computation**.**

To overcome these limitations, the proposed A2Res-CNN model is implemented. Using this method to detect breast cancer involves a collaborative effort across multiple disciplines, leveraging domain expertise from medicine, computational techniques from computer science, and data processing and analysis methods from data science. This interdisciplinary approach ensures the development of accurate and clinically relevant breast cancer detection systems that can assist healthcare professionals in early diagnosis and treatment planning.

The input image from the MIAS and the CBIS-DDSN datasets is fed into the pre-processing process to strengthen the brightness of the source using image enhancement. The pre-processed image is then subjected to feature extraction with a modified attention module of both channel and position attention based on ResNet50. These attention modules enhance the extracted feature representation. The concatenate feature output is employed in the A2Res-CNN to classify the lesion tissues. The block diagram of the A2Res-CNN model is presented in Figure 1.

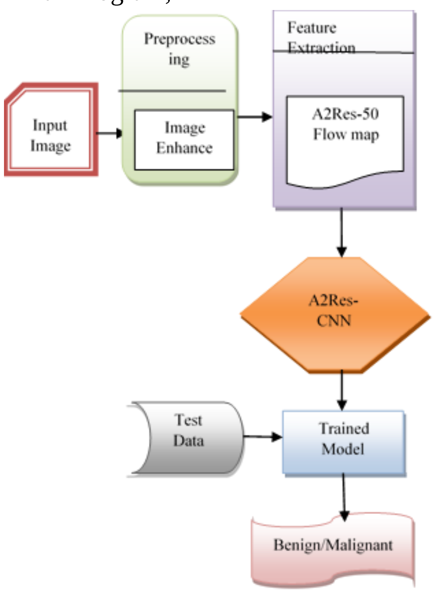



**Fig 1:** Block diagram of A2Res-CNN model for detecting breast cancer

### 3.2 Input

The input source is obtained from the dataset of MIAS and CBIS-DDSN. In Mammographic Image Analysis Society (MIAS) [19] consists of 161 pairs of 322 original images in portable gray map (PGM) format with 50-micron resolution. Another one is the CBIS-DDSM [18] is a huge-scale dataset containing 2,620 cases of mammographic images. The attained input is mathematically expressed as,

$$M = \{s_1, s_2, \ldots. s_i, \ldots. s_n\} \tag{1}$$

Where $M$ denotes the database with image input is represented as $\{s_1, s_2, \ldots.., s_i, \ldots. s_n\}$.

### 3.3 Pre-Processing

The input mammographic sources are subjected to the pre-processing system to enhance the image with inclusive brightness for training. To obtain an efficient image, the image enhancement process is performed in this pre-processing block. The process of enhancing the image for evaluation purposes is defined as image enhancement. In image enhancement, the visual quality of the image is effectively improved by making the image clearer and sharper with brightness 10 and adjusting the image contrast to 2.3, which eradicate the unwanted noise present in the input image source. The resultant outcome of the pre-processing system is denoted as $E$ .

### 3.4 Feature Extraction

The pre-processed image is then fed into the extraction process, which compresses the unwanted illustration of the image. The feature extraction of the mammographic images includes the A2Res-50 feature flow.

#### 3.4.1 ResNet 50

The ResNet50 architecture is merged with the attention module layer to effectively improve the model performance. The ResNet50 model contains the convolutional layer, max pooling layer, ReLU layer and batch normalization layer. The prior layers are termed BaseNet together with the global average pooling layer for categorize the input image. The feature map is extracted by the BaseNet model. In these two branches of attention mechanism are developed in which the primary attention branch generates the attention probabilities whereas the second one applies the probability of feature vector. At last, the resultant outcome obtained from the attention is concatenated with the feature flow map for improved performance of model efficiency [21]. The architecture of A2Res-50 is illustrated in Figure 2 [20].

To attain a better feature vector the outcome of ResNet 50 is combined with the channel and positional attention module, which is briefly explained in below sections 3.4.1 and 3.4.2. These concatenated outcomes of the feature extraction are expressed as, $B$ .

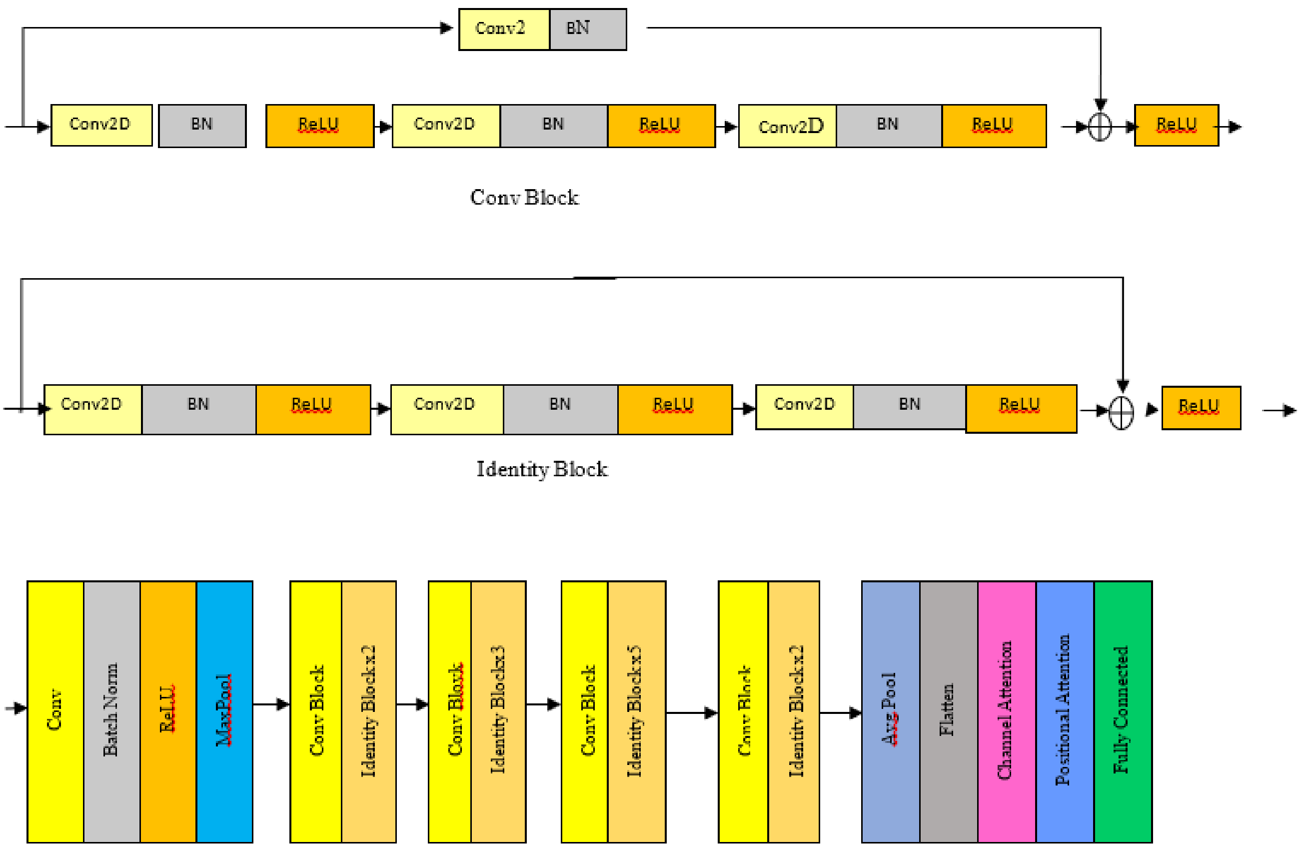



**Fig 2:** Architecture of A2Res-50

### 3.5 A2Res-CNN model

The most common used method for breast cancer detection is evaluated by CNN. In this method, the images obtained from the feature extraction are evaluated for the detection process. Breast cancer is detected by the model by a CAD system to extract the features and detect the lesion tissues as malignant or benign cells. For large datasets, the CNN model consumes more time, high computation cost, and also causes over-fitting problems. To overcome these limitations and also automatically detect breast cancer from the lesion region we propose a A2Res-CNN model, together with the A2Res-50 to improve the efficiency of model performance. The improved model performance with efficiency occurs to the channel and positional attention mechanism. The architecture of the A2Res-CNN model is structured in Figure 3.

The input of the A2Res-CNN architecture is obtained from the extracted outcome. The feature outcome of the extracted image is accomplished by the A2Res-CNN model. These inputs are fed into the layers of convolutional, max-pooling, and ReLU. The obtained result of the layer is allowed into the attention mechanism. The enhanced efficient result is provided in the dropout parameter to the flattening layer. Finally, the outcome is attained from the fully connected layer which detects the breast cancer effectively.

#### 3.5.1 Channel Attention Module

The high resolution of mammographic images generates a feature flow map $F_s$ ,with multi-channel resolution , $P$ is the number of channels with height $Q$ , and width $R$ . These feature flows are subjected to various convolutional layers, and the information obtained from each channel feature map is distinct. In this channel attention module, low-level resolution images are accurately achieved to the semantic high-level resolute image. The feature obtained from each channel is related together with the corresponding channel. In each channel, the global max pooling and average pooling generate the information on spatial dependencies representation. These feature descriptors are fed into the hidden layer of MLP and provide significant feature vectors with high-frequency components. The details achieved in high-frequency components include texture details, region details, edge details, and so on. Thus outcome feature vectors are integrated with the sigmoid function and the resultant outcome is defined as a channel attention map. The mathematical expression of the channel attention module is defined as,

$$T = Q_{gp}\left(B\right) = \frac{1}{Q \times R}\sum_{a=1}^{Q}\sum_{b=1}^{R} B\left(a,b\right) \tag{2}$$

Where, $B(a,b)$ is the input obtained from the feature extraction with the position value of $(a,b)$, $Q_{gp}$ defines the global average pooling function. The image and local descriptors information are aggregated with several techniques without a global pooling function. The obtained information is then introduced into the gating mechanism. This gating mechanism includes the channel non-linear interactions and one-hot activation is opposed by the multi-channel features to attain the non-mutually-exclusive relation. Thus the gating mechanism is expressed together with the sigmoid function

$$k = \sigma\left(l\psi\left(mT\right)\right) \tag{3}$$

Where $\sigma$ is the sigmoid function, $\psi$ is the ReLU function, $l$ and is the convolutional layer weight after performing the ReLU function the low-resolution signal is increased to a high-dimensional signal with channel-upscaling layer. thus the weight of the channel-upscaling layer is denoted as $m$. The obtained result of the channel dependencies is $k$ which is rescale from the input $s_i$ . The scaling factor of the feature flow of channel attention is expressed as,

$$\widehat{B} = k_c . B_c \tag{4}$$

Where, $k_c$ and $B_c$ are the scaling factors.

#### 3.5.2 Positional attention module

In the positional attention module, the query and the key value are represented in sequential form. By this query and key value, the positional attention is measured by adding the weighted sum together with the similar values of query, value, and keys. The sequential features of positional information dependencies are mathematically expressed as,

$$PA\left(G^u, G^e, G^v\right) = soft\max\left(\frac{G^e\left(G^u\right)^T}{\sqrt{f_d}}\right)G^v \tag{5}$$

Where, $G^u, G^e,$ $and\, G^v$ are the sequential representation of query, key, and value respectively, and $f_d$ denotes the feature dimension of each value. The concatenated result of the linear layer feature together with the fixed dimensional feature is mentioned as the outcome of the positional attention mechanism.

$$W = concatenate\left(t_1, .......t_n\right)N_o \tag{6}$$

$$t_i = PA\left(GN_i^u, GN_i^e, GN_i^v\right) \tag{7}$$

Where, $N_i$ and $N_o$ are the parameters obtained from the positional operation. The features are attended by the combined layers of two convolutional layers together with the ReLU activation layer. The resultant output of the positional attention mechanism is defined as,

$$P = \mathrm{Re}LU\left(\left(C + D\right)N_1 + d_1\right)N_2 + d_2 \tag{8}$$

Where, $C$ denotes the normalization layer and $D$ defines the sine and cosine functions of distinct positions. $N_1$ and $N_2$ are the convolutional function with bias $d$ .

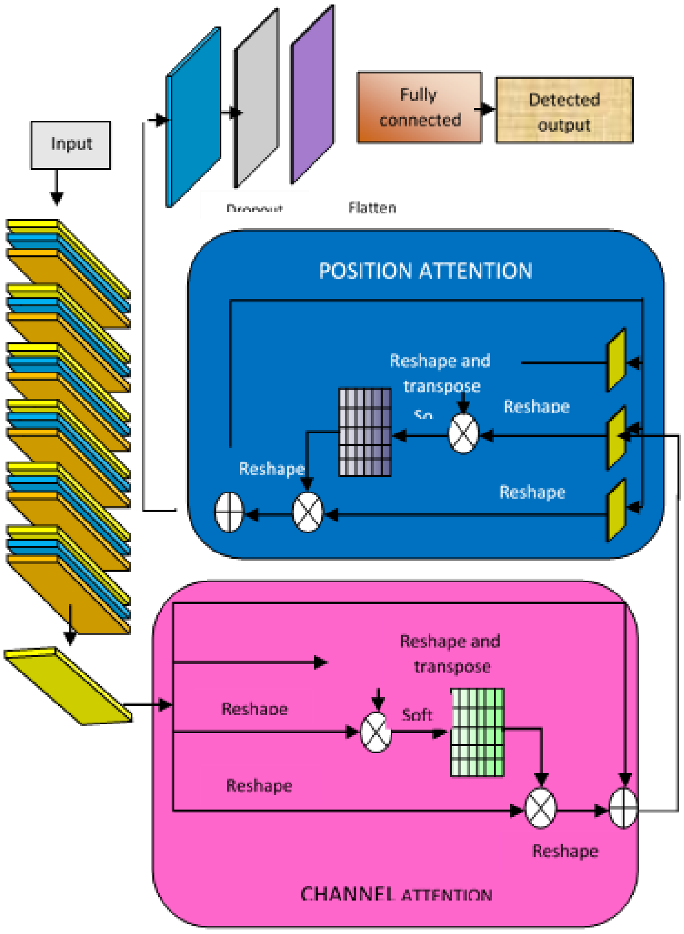



**Fig 3:** Architecture of A2Res-CNN Mo

### 4. Results

This section elaborates on the experimental outcome of the A2Res-CNN, along with its comparative and performance evaluation by considering the training percentage values.

### 4.1 Experimental Setup

This experiment is implemented in PYTHON interpreter version 3.9 which consists of several programming methods and techniques with pycharm 2023.2.5 software, which is evaluated in Windows 11 Pro with 16GB RAM and 128 GB ROM.

### 4.2 Data Description

This research aims to automatically detect breast cancer with an applied database of CBIS-DDSM and MIAS.

**a) CBIS-DDSM [18]:** The CBIS-DDSM contains 2,620 cases with mammographic images, which includes information on normal, benign, and malignant studies. The dataset is widely used for testing and developing the decision support system. The dataset contains a subset which carefully curated for trained mammographers. The images present in this database are compressed into DICOM format.

**b) MIAS [19]:** In Mammographic Image Analysis Society (MIAS) consists of 161 pairs of original images in obtained in the PGM format with 50-micron resolution.

### 4.3 Experimental Results

The experimental results of the input image are pre-processed and the featured ResNet is illustrated in Figure 4.

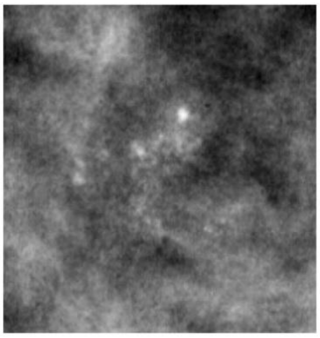
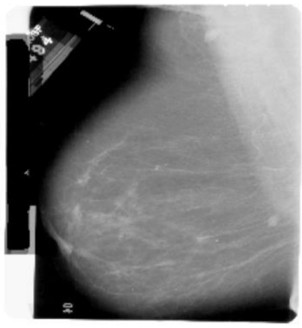
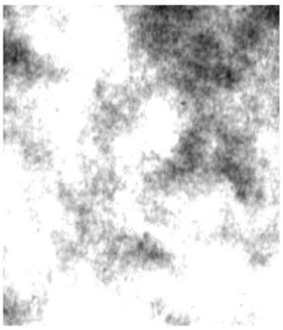
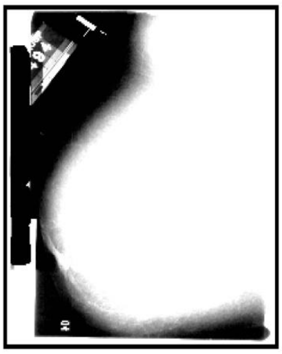
| Method | Sample 1 | Sample 2 |
|---|---|---|
| Input image source |  |  |
| Pre-Processed image |  |  |
| ResNet-50 |  |  |

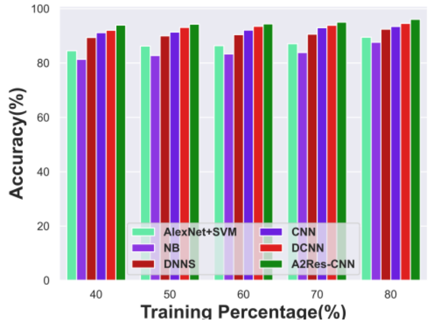
**Fig 4:** Experimental results of A2Res-CNN model

### 4.4 Comparative Methods

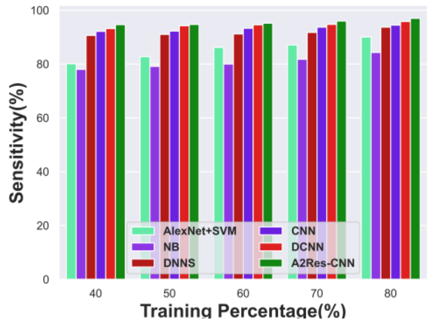
The evaluation of the A2Res-CNN model is resembling with the existing classifiers as, AlexNet with SVM classifier [22], NB [23], Deep Neural Network [24], CNN [25], and DCNN [26] classifier methods with CBIS-DDSM and MIAS dataset provides the comparative results with access of training percentage evaluation. The evaluated metrics are accuracy, sensitivity, and specificity.

#### i) Comparative evaluation of TP for the CBIS-DDSM dataset

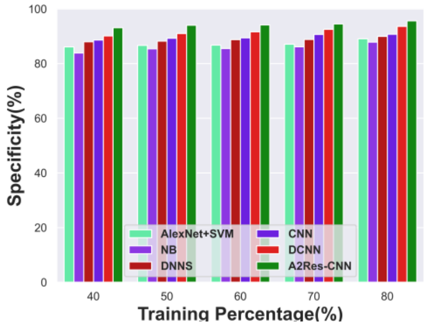
The A2Res-CNN model was examined with CBIS-DDSM dataset are achieved with the training percentage evaluation. The comparative estimation of the experimental model with other existing classifier methods generates the comparative outcome for accuracy with TP of maximum value as 80 will attain the comparative value for accuracy is 6.85 %, 8.77 %, 3.79 %, 2.76 %, and 1.56%. For sensitivity, the TP value is 80 attains the results as 7.15 %, 13.09 %, 3.38 %, 2.60 %, and 1.23 %. For specificity, the maximum TP value for 80 in the obtained outcome is 6.86 %, 8.14 %, 5.96 %, 5.14 %, and 2.12 %. The comparative results of TP of various existing methods are organized in Figure 5.




Accuracy




Sensitivity

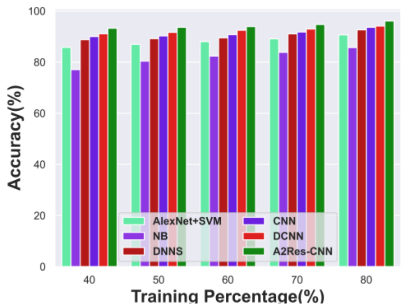



Specificity

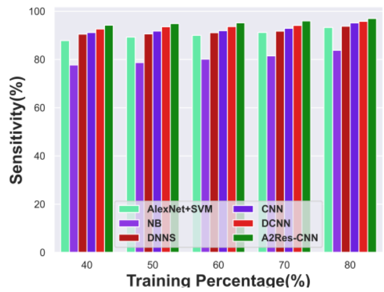
**Fig 5:** Comparative evaluation of CBIS-DDSM dataset

**ii) Comparative evaluation of TP for the MIAS dataset**

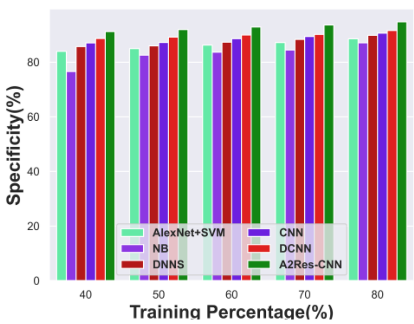
The A2Res-CNN model was examined with the MIAS dataset are achieved with the training percentage evaluation. The resembling estimation of the experimental model with other existing classifier methods generates the comparative outcome for accuracy with TP of maximum value as 80 will attain the comparative value for accuracy is 5.65 %, 10.82 %, 3.61 %, 2.59 %, and 2.07 %. For sensitivity, the TP value is 80 attains the results as 3.84 %, 13.57 %, 3.31 %, 1.88 %, and 1.23 %. For specificity, the maximum TP value for 80 in the obtained outcome is 6.55 %, 8.12 %, 5.23 %, 4.38 %, and 3.36 %. The comparative results of TP of various existing approaches are organized in Figure 6.




Accuracy




Sensitivity




Specificity

**Fig 6:** Comparative evaluation of the MIAS dataset

### 4.5 Comparative Discussion

This section states the comparative estimation discussion of the A2Res-CNN model together with other existing methods.AlexNet with SVM classifier does not perform effectively for large-scale datasets, and provides noise and overfitting problems. It also caused less inference time with high computational cost. Naïve Bayes (NB) had the major limitation that accessed by a zero-frequency problem. The input dataset is under the training process and is classified into a diverse variable in this for zero probability the assigned variables are not available. DNN classifier requires a huge amount of data to attain the training process, whereas CNN classifier also requires a large dataset for the training process, which leads to high computation cost and time. In DCNN method involves large-scale data requirements which results in maximum time consuming. To avoid those overall issues the proposed A2Res-CNN model is implemented for detecting the breast cancer with the evaluation of mammographic images. The DCNN method is also time time-consuming process with a huge amount of data requirements. To overcome these challenges, implemented an A2Res-CNN model for detecting breast cancer with mammography evaluation. The comparative assessment discussion of the A2Res-CNN model with the existing techniques and methods for CBIS-DDSM and MIAS datasets. The comparative estimation of the proposed A2Res-CNN is mentioned in Table 1.

**Table 1:** Comparative assessment discussion of the A2Res-CNN model

| **Methods** | Training Percentage | | | | | |
|---|---|---|---|---|---|---|
| | CBIS-DDSM | | | MIAS | | |
| | Accuracy (%) | Sensitivity (%) | Specificity (%) | Accuracy (%) | Sensitivity (%) | Specificity (%) |
| AlexNet+SVM | 89.51 | 90.06 | 89.09 | 90.69 | 93.28 | 88.59 |
| NB | 87.67 | 84.3 | 87.87 | 85.72 | 83.84 | 87.10 |
| DNN | 92.46 | 93.72 | 89.95 | 92.65 | 93.79 | 89.85 |
| CNN | 93.45 | 94.48 | 90.73 | 93.63 | 95.18 | 90.65 |
| DCNN | 94.60 | 95.8 | 93.62 | 94.13 | 95.8 | 91.62 |
| Proposed Attention Ensemble-DCNN | 96.10 | 97 | 95.65 | 96.12 | 97 | 94.80 |

## 5. Conclusion

The research introduces an A2Res-CNN model for detecting breast cancer with an A2Res-50 in feature extraction which generates an accurate and robust breast cancer detection. The integration of channel and position attention modules strengthens the model performance ability, while the use of deep features contributes a complex tumour patterns with high delineation. Thus experimental outcomes enhance the efficiency of the A2Res-CNN model over prior traditional methods. The model provides an enhanced feature extraction with reconstructed image to achieve the overall evaluation of the model. This paper provides a remarkable development in breast cancer detection. By comparing the proposed model together with other traditional methods the obtained results denote the improved performance with evaluation metrics like accuracy, sensitivity, and specificity. Further testing and validation of widespread clinical applications are extended in future studies.

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