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University College Cork, Ireland
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Advance ANN Algorithm and Research Challenges for Breast Cancer Detection and Classification with evaluation NI LabVIEW

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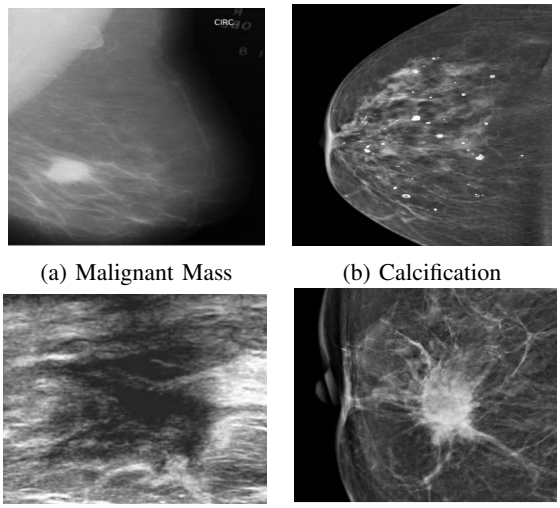
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***Abstract*—Machine learning and digital image processing are hot emerging technologies which have garnered a lot attention for the past few decades because of promising results in multi fields like electronics, medical, communication and vision.Deep learning which is subclass, has been used for the classification for the natural images has gained a lot of research interest among biomedical researchers for better estimation of medical diagnosis. In this research paper, we developed and implemented a deep learning algorithms with image processing for detection of breast cancer in the early stage using by utilization of the algorithms in X-ray mammograms images during diagnosis. The information parameters include background tissues, abnormality, severity of classes, and etc. The algorithm utilized neural network for the model training and implementation performed in LabVIEW NI vision toolkit. The proposed algorithm performed better results and promising with excessive training of the images.Finally, we proposed novel research challenges and open problems in this area which requires further research and investigation by researchers.**

***Index Terms*—Classification, Deep Learning, Digital Image Processing,LabVIEW, Machine Learning, Neural Network, Artificial Neural Network, Algorithms Design**



(a) Malignant Mass (b) Calcification

(c) Architectural Distortion (d) Spiculated Mass

Fig. 1: Classes of Abnormalities

I. Introduction

According to World Health Organization (WHO), women under the age of 60 are affected by the cancer of the breast followed by the cervix, lungs and stomach [1]. According to a study in 2016, around 0.25 million female were diagnosed with breast cancer in them [2]. For this reason much research has been carried out over the years for the early detection and removal of this disease that has been greatly affecting the human population. For many years, breast cancer has posed a serious global threat to women which is prevalent and raised concerns among researchers in the medical field. Biomedical research is getting advanced and requires the latest research methodologies to predict cancer cells. The latest advancements in technology and integration of the latest image-processing tools within biomedical devices have opened the gates for the latest research mythologies. Separation of normal cells to tumor cells in early stages can be done by utilization of advanced image and machine learning techniques. Early stages of detection and prevention of the disease become highly complicated due to unknown causes like the patient's body, diagnosis tools, and some other factors. Despite this fact, certain regular indicators like the

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existence of different types of the masses and classification of different types of mammograms can serve as important early indicator tools that can provide essential measures to be taken on time. The architectural formations and marginal properties are considered for this category. Abnormalities can be of calcification symptoms, circumscribed object masses, speculated objects with masses, ill-defined shapes, architectural distortion in masses ,asymmetry and normal as shown in Figure 1. To begin with, a cancer is simply a cell mass that no longer follows the growth and division pattern of a normal healthy cell. This pariah mass then grows, starts to multiply and affects the neighbouring cells. When the mass reaches to a substantial size, it is considered to have been 'metastasized' because it would then have the ability to spread onto other tissue cells [3]. Therefore preliminary screening tests on X-ray mammograms is of paramount importance for the sustenance of human lives. Specifically for cancers of the breast region, the first major category is its severity category including malignant and benign. In this case the morphological dimensions and features are evaluated. A malignant cancer is one which can harm the human body while a benign cancer is one which has an abnormal growth but is otherwise harmless to the human body, save a mild level of pain. Second major category is the abnormality type.The third most important category is considered to be the background tissue. Whether the breast area lesion is fatty, fatty and dense glandular. Though the medical investigation of X-ray mammography is an considered accurate and efficient way for breast cancer detection, it is not absent with flaws and misinterpretations [4]. With the advancement of soft computing techniques, a new field of medical image processing has come into focus for researchers. Using image processing features, the realization has made it easy to detect cancerous masses from infected areas of the breast. Some of the image segmentation techniques for breast cancer detection include texture segmentation on early-stage tumor [5], image averaging and threshold [6], fuzzy logic and neuro-fuzzy logic system for image features extraction [7], etc. With advancements in machine learning research, researchers have dived into the world of deep learning (DL) to further classify cancer with a higher order of accuracy and less computation time. Deep learning (DL) has become a subclass of (ML), in which multiple groups of techniques are formed in which the system learns from the inputs given by modeling the parameters. The methodology is implemented by creating a system model and then performing the classification of a new input as per the pre-defined model. Deep learning is currently being utilized in multiple medical fields such as bioinformatics [8], Alzheimer's diagnosis [9], Sepsis prediction [10], etc.

A. Previous Related Work

In the past years, technological advancement in digital signal processing tools and artificial intelligence algorithms has opened ways to early detect the breast cancer by merging the research algorithms performed in software tools like LabVIEW and MATLAB in biomedical devices. *Kourou* [17], provided a detailed review of ML techniques which are employed to enhance cancer prognosis and prediction in breast. The authors emphasized classification groups and categorized into risk groups, which are important for effective clinical management.Authors discussed ML methods, including supervised and unsupervised learning, and their applications in analysis complex biological data to predict cancer outcomes including pattern and biomarkers. *Duygu Kaya and Mustafa Turk* [18],presented a novel predictive model for cancer prognosis. The model utilized a cascade framework approach to integrate algorithm with LabVIEW to process complex biomedical data with parallel processing .By utilizing the statistical mechanics and machine learning, the research provided a robust system which was capable of predicting cancer outcomes with high accuracy.*Z. Wang* [19] presented a breast cancer detection approach with implementable framework that combines convolutional neural network(CNN) deep feature extraction with a classifier. The proposed fusion approach enhanced the accuracy of breast mass detection. This method demonstrated significant potential in improving diagnostic precision with maintaining computational efficiency. *H. Priya M. and S. Krishnaveni*, introduced a breast cancer detection system utilizing LabVIEW for biomedical monitoring with model formation [20]. The system applied the Watershed Algorithm to MRI and CT scanned pictures to identify and locate tumor positions with accuracy This framework enhanced digital image processing capabilities, enabling accurate and efficient detection of breast cancer in women.*Prerita and N. Sindhwani* [21] presented the article which evaluated various machine learning algorithms for breast cancer detection. The study compared models based on accuracy,applicability and performance. The authors highlighted the effectiveness of machine learning algorithms in improvement of early diagnosis of cancer. The findings underscored the potential of ML tool and techniques for enhancing clinical decision-making in breast cancer detection. *Arnob, Md Wahiduzzaman Khan* [22] presented a hybrid model combining Principal Component Analysis (PCA) and Multilayer Perceptrons (MLP). This approach reduced computations overhead and complexity while performing the accurate predictions in early breast cancer detection. The research demonstrated the model's importance for efficient and reliable diagnostic applications. *Adam* [23],reviewed the advancements in DL techniques and tools for breast cancer detection using MRI images.The article highlighted significant development in improving diagnostic accuracy and efficiency. However, the study noted pitfalls such as limited generalizability, lack of standardization, and challenges in clinical translation which require large datasets. *Mohammed* [24], introduced a deep learning model for classifying breast cancer types using ultrasound image. The research methodology showcased the potential of deep learning in enhancing diagnostic precision and non-invasive detection. However,the proposed algorithm had reliance on limited datasets, which may not represent diverse patient populations, and challenges in adapting the model for real-world clinical. *Maistry* [25] evaluated various deep learning models, including CNNs and

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TABLE I: Overview of Previous Algorithms

Authors	Sensitivity
Radiologists [11]	88.89%
Shi [11]	86.11%
Varela [12]	88.00%
Dominguez [13]	80.00%
Bellotti [14]	80.00%
Cascio [15]	82.00%
Oliver, A. et al. [16]	83.00%

Vision Transformers (ViTs), for breast cancer detection. The article found that ViTs outperform CNNs with a diagnostic percentage of more than eighty percent. However, authors work included the high computational cost of ViTs, the need for large labelled datasets for training, and challenges in model interpretability, which limited their immediate applicability in clinical settings. *Esfahani* [26] in the research artilce provided an extensive review of deep learning applications in breast cancer detection across multiple imaging modalities. It highlighted advancements in diagnostic accuracy and efficiency. *Hussain S* [27] in research article systematically reviewed machine learning techniques for breast cancer risk prediction. It pointed out the ability of ML models to analyse complex risk factors and improve prediction accuracy compared to traditional methods. However, the article identified the pitfalls of the methodologies including need for the large data sets and standardizations.The review article also emphasized the limited interpretability of some ML models, which may obstruct their integration into clinical decision-making processes.The Table I presents the overview of the previous work and sensitivity percentage.

B. Contribution of Research Paper

The contribution of the research article paper are as follows:

1) The research article presents machine algorithm and implementation strategy for the early detect and classify types of breast cancer using deep learning algorithms.
2) Secondly, the presented algorithm has been implemented with all steps and the model has been trained for the classification using NI LabVIEW Machine learning toolkit. Algorithm results were compared with previous models and improvement methodology has been proposed.
3) Finally, the research paper investigates the novel research challenges and open problems that require future research in the filed of machine learning and advanced digital image processing techniques.

II. Proposed Algorithm

The implementation of advanced deep learning algorithm for breast cancer detection using LabVIEW involved several steps. First, datasets which were mammograms scans were collected and annotated, ensuring diverse and balanced samples. The data undergoed preprocessing, including noise reduction, normalization, and augmentation, to enhance its quality and variability. Segmentation techniques like Watershed were used too isolate regions of interest. A robust deep learning model,Artificial Neural Network (ANN) was trained using frameworks of LabVIEW. After training, the model was exported in a compatible format for integration with LabVIEW. Real-time data from medical imaging devices was preprocessed in LabVIEW and passed to the deep learning model for predictions. The results, including detected regions and classifications, were visualized on LabVIEW's interface, aiding in clinical decision-making. Post-processing techniques generate diagnostic reports with actionable insights for clinicians. The system undergoes rigorous testing for robustness, accuracy, and clinical validation to ensure reliability.The algorithm steps are shown in as shown in Figure 2.

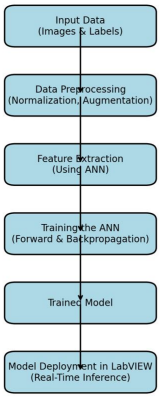


Fig. 2: Algorithm Flow

A. Data Set

An ANN requires a large amount of data-set for a highly accurate prediction. Due to less availability of a large data-set, the network is to be trained with the presently available data on the internet. 322 images were used from [11], actual size of which is 1024 x 1024. Class bifurcation is such that 133 images are abnormal and the rest 189 images are of normal breasts. From the abnormal class 21 images are of increased density mass, 22 images are of architectural distortion, 24 images of calcium development in the breasts, 24 images are for circumscribed masses, 24 images are for speculated masses and the remaining 18 images are classified as miscellaneous class with no confirmation of malignancy. Training is to be done on 70% of the complete data set and 30% would be the testing dataset. Images available which are in greyscale would be preprocessed and segmented in such a way that features can be extracted and then the neural network is trained and tested.

B. Algorithm Applicability

The Advanced ANN Algorithm for breast cancer detection and classification is designed to process data from multiple

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imaging modalities, such as MRI, ultrasound, and mammograms. Its adaptability across these imaging techniques plays a crucial role in determining its generalizability. MRI scans provide high-resolution soft tissue contrast, while ultrasound is commonly used for real-time, cost-effective screening.Compared to traditional rule-based detection systems, the ANN model learns non-linear representations, making it inherently more flexible. However, domain adaptation techniques may be necessary to prevent performance degradation when applied to new datasets from different imaging sources.

III. Implementation with Image Preprocessing and Segmentation

For the breast cancer detection algorithm digitized image is necessary which was feed to the algorithm.

A. Preprocessing of Images

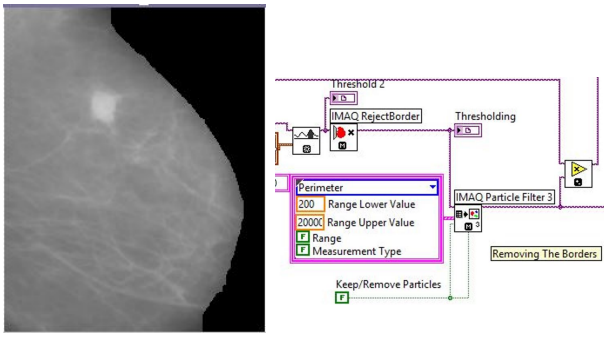
For making the same quality level and synchronized the colouring balances preprocessing of the images is crucial step.Therefore, this step is applied on the digitized samples image to perform the preprocessing to improve the quality of image without compromising on the detection features for diagnosis as shown in Figure 3. Using the image enhancement functions,filtering and morphological operations are performed in this stage as well in order to make the images sizes same and remove unwanted areas.

1) Dimensional Median Filtering: The process of highlighting significant characteristics and eliminating undesirable ones is known as image filtering. The median filter is one of the non-linear spatial filters that has been utilized to lessen unnecessary noise spots in the input image. This filter is helpful for eliminating random noise while maintaining edges. The median value, which may be determined by sorting the original image's pixels and then using the middle value of the sorted pixels to replace the pixel value, is utilized in this approach to replace the image's pixels. The mean of two pixels will be determined if the number of pixels is even. When the median value has been used to replace every pixel in the original image, the replacement process will come to an end. Figure 4 shows the effect before and after filtration.

B. Segmentation of Images

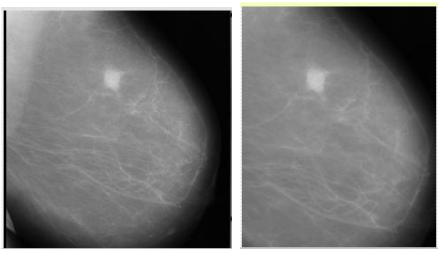
The area of interest (ROI) segment must be improved for better breast cancer detection results, which means the segmentation step of the detection algorithm confirms the highly successful. Segmentation was used in this procedure to separate the pectoral muscle, the breast, and any suspected pathological masses. Different regions of interest are produced as a result of this segmentation procedure. The region of interest, or final mass segmentation findings, are displayed in Figure 5.

1) Global Threshold: Because the methods are simple, global thresholding has been used in the results images. It is based on the image's global information and selected a one threshold value for the entire digital image. The global threshold predicted value was easily considered as the abnormality patches have higher intensity values than the nearby tissue. As mentioned in [8], the histogram of the healthy regions in



(a) Preprocessed Image (b) Boarder Rejection

Fig. 3: Preprocessing Flow



(a) Original Image (b) After Median Filtering

Fig. 4: Before and After Removing Noise in Images

the targeted areas has a single peak, while the histogram of the abnormality regions displays several peaks.Global thresholding was used because it assigns a single class to all pixels that fall inside a specific range.In global thresholding process, initial estimate of threshold value T was selected. After that segment the image using value of T. This process converted the pixels of an image into two groups: Pixels having value greater than T were considered as cluster 1 and pixels having value less than 1 were considered as cluster 2. After which we calculated average value from each cluster and calculate new value T_{new} using 1:

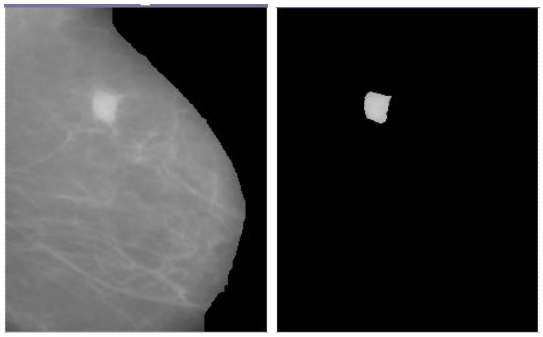
$$T_{new} = (mean_1 + mean_2)/2 \quad (1)$$

Where $mean_1$ and $mean_2$ are the mean values of cluster 1 and cluster 2 respectively. This process will continue until the value of T becomes very small.

C. Feature Extraction and Selection

The third phase in this section of the breast cancer detection algorithm is feature extraction and selection. The region of interest's most crucial characteristics are chosen for classification. Because intensity features are discriminative and may reliably distinguish between benign and malignant tumours, their selection is crucial. LabVIEW and MATLAB tools were utilized as software is widely used for testing and instrumentation [28]–[35].The LabVIEW GUI for the retrieved features and histogram is displayed in Figure 6.

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(a) Grayscale Image of Segmented Breast (b) Segmented Mass

Fig. 5: Segmented Mass Grayscale Image

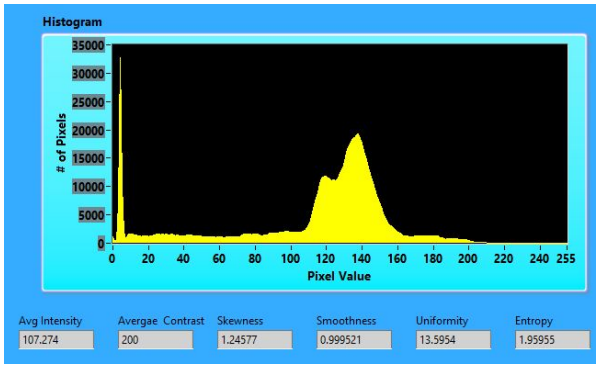


Fig. 6: GUI View of Feature Extraction

1) Intensity of the Image Features: Histogram of the intensity levels help us to extract these types of features where ere used to crease input labels.

2) Mean: The average intensity was calculated using the equation 2.

$$[m = \sum_{i=0}^{L-1} z_i p(z_i)] \tag{2}$$

where p(z) is the grayscale image's histogram and z is a random intensity value.

3) Standard Deviation Estimation: Standard deviation has been calculated using equation 3:

$$[\sigma = \sqrt{\mu_2(z)}] \tag{3}$$

4) Third moment: Third moment gives the symmetry of histogram also known as skewness of histogram which can be calculated using equation 4:

$$[\mu_3 = \sum_{i=0}^{L-1} (z_i - m)^3 p(z_i)] \tag{4}$$

5) Smoothness Calculations: Smoothness of measured values is calculated in segmented mass. The calculated value of smoothness (R) was taken as zero for region of contrast intensity and becomes one when the focused region had significant excursions intensity levels.

$$[R = 1 - (\frac{1}{1+\sigma^2})] \tag{5}$$

6) Uniformity Estimation: At the point when all grey level same values (maximum uniform), this metric reaches its maximum; otherwise, it falls as inequality increases. The calculation of homogeneity is explained by the following expression:

$$[m = \sum_{i=0}^{L-1} p^2(z_i)] \tag{6}$$

7) Estimated Entropy : The entropy values was calculated in order to calculate the randomness as calculated by equation 7.

$$[m = -\sum_{i=0}^{L-1} p(z_i) log_2 p(z_i)] \tag{7}$$

D. Classification Stage

The final step in the algorithm for detecting breast cancer was classification. This step involved classifying the segmented mass to be categorized as benign mass or malignant mass by feeding the chosen and extracted listed features into a classifier.

1) Artificial Neural Network Model and Training: The segmented mass was classified using an artificial neural network (ANN) with back propagation. The three primary layers were the output layer, which identified if the mass was benign or malignant, the hidden layer and the input layer, which contained the features we had chosen. The elements of a typical neural network are depicted in Figure 7. To

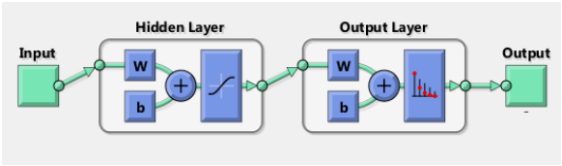


Fig. 7: Neural Network

find breast cancer, a back-propagation neural network was used. In order to obtain the intended output, the feed-forward artificial neural network (ANN) with supervised learning algorithm labelled the input values that were fed into the learning machine model with the type of mass class. Sixty-five percent of the datasets were fed into the neural network as "Inputs" throughout the training process. Additionally, the neural network was fed the target matrix, which had two values: 0 for a benign tumour and 1 for a malignant mass. The data samples and GUI of LabVIEW shown in Figure 8 and as shown in Figure 9 respectively. The confusion matrix expression was produced as a gauge of the neural network's performance following the training of every sample. Four numbers make up the confusion matrix: True Negative (TN), False Negative (FN), and False Positive.

$$ConfusionMatrix = \begin{bmatrix} TN & FN \\ FP & TP \end{bmatrix}$$

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SD	Contrast	MEAN Int	SKEWNES	UNIFORM	SMOOTNE	ENTROPY	Class
27.504	4.1	212	-6.704	0.999	0.773	0.079	1
44.129	11.283	209	-3.703	0.999	2.075	0.211	1
39.79	10.464	197	-3.609	0.999	1.693	0.201	1
69.457	33.143	216	-1.646	1	5.923	0.532	1
28.969	5.02	201	-5.67	0.999	0.864	0.107	1
50.154	17.393	186	-2.585	1	2.818	0.3	1
34.524	7.868	182	-4.256	0.999	1.254	0.159	1
7.551	0.426	151	-18.203	0.983	0.057	0.014	1
50.85	14.532	220	-3.28	1	2.797	0.235	1
28.587	5.008	199	-5.676	0.999	0.842	0.105	1
13.53	1.254	168	-10.866	0.995	0.185	0.036	-1
46.068	12.099	214	-3.602	1	2.269	0.209	-1
41.907	8.739	233	-4.641	0.999	1.833	0.15	-1
44.962	11.22	215	-3.804	1	2.147	0.195	-1
14.578	1.138	202	-12.875	0.995	0.214	0.025	-1
40.125	9.054	211	-4.251	0.999	1.692	0.158	-1
41.647	9.405	221	-4.248	0.999	1.823	0.167	-1
41.557	11.821	184	-3.273	0.999	1.867	0.233	-1
55.708	16.763	225	-3.057	1	3.384	0.261	-1
20.063	2.028	214	-9.879	0.998	0.407	0.039	-1

Fig. 8: Data Sets Sample

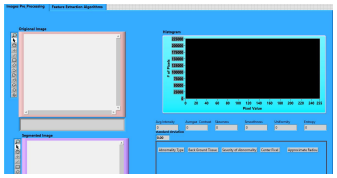


Fig. 9: LabVIEW GUI

IV. Results

Seventy-five percent of the samples were trained correctly. During the training phase, the neural network's performance was approximately 98%. The remaining 25% of the samples were examined to see whether they contained benign or malignant tumours.The following overall confusion matrix findings were generated by comparing the resultant matrix data of the examined mammography images with the output data matrix was produced by the neural network during the test and trial phase. However, despite being identified as cancer by a biopsy, some mammography images were missed (FN) and categorized by algorithm as benign by the neural network. Additionally, despite being classified as benign by a biopsy, the neural network misinterpreted some mammography pictures (FP) as malignant. The cancer photos that were missing are displayed in Figure 10.



(a) Missed Dataset 16 Image (b) Missed Dataset 92 Image

Fig. 10: Missed Cancer Images

Figure 11 presented the false and miscalculated images which were benign but classified by algorithm as malignant. A low false negative and false positive value is necessary for an accurate diagnosis since a high false negative value indicates that malignant masses were overlooked during the handling procedure, while a high false positive value



(a) Misinterpreted Dataset 08 Image (b) Misinterpreted Dataset 20 Image

Fig. 11: Misinterpreted Cancer Images

indicates that benign masses were mistakenly diagnosed as cancer.

V. Research Challenges and Open Problems

Some of key challenges in networking for indoor UAVs are discussed as follows:

1) Due to lack of large, annotated datasets for diverse populations it becomes very difficult to train model with large variety of the data sets.Imbalanced datasets, where benign cases vastly are more than malignant ones, leading to biased models formation.Variability in imaging quality with different devices and institutions.Ethical concerns and regulatory requirements (e.g., HIPAA, GDPR) make it difficult to access sensitive medical data. Need for privacy-preserving ML techniques, such as federated learning.
2) Model generalization is another challenge in which there is difficulty in developing models that generalize well across different imaging modalities (e.g., mammograms, MRI, ultrasound). Challenges in adapting models trained on one dataset to other datasets or populations.Also there are lack of transparent models that can provide interpretable results for clinicians and biomedical devices.Need for techniques like attention maps or saliency visualization to explain decisions.
3) Open research challenges include the real-rime implementation challenges and computational efficiency in embedded system board of biomedical devices.High computational costs associated with deep learning models in real-time processing requires GPUs and high ended processing capabilities.Optimization of ML models for deployment on low-power DSP hardware or edge devices.

VI. Conclusion

In this research work presented, we proposed the machine learning algorithm in which artificial neural network was utilized with back propagation algorithm. The research study compared the previous work presented and identified the gaps in published work. We developed the model and utilized the open sources mammographic images.Labview NI image processing toolkit and vision functions were used to implemented the algorithm and applied filters.The model

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training was done with more than thousands of the images and categorized the types of abnormalities which was not previously done with highly accuracy.Finally, we presented the research challenges and open problems in the area of digital signal processing and machine learning utilization for the breast cancer detection and implementation.The future will incorporate the further training on the data with more samples and GPU for higher accuracy.The dataset with accurate acquisition of images for the real time processing and implementation with clinical validation will be the future direction.

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