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Improved cancer detection in mammogram images using automated Deep Learning Technique

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Abstract— Mammography is an exceptionally normal screening apparatus for diagnosing breast growth at beginning time as compare to other screening techniques to reduce female death rate. The techniques and algorithms that were extensively used are convolution neural networks, artificial neural networks, support vector machines, and so on. A comparison pertaining to the supremacy of deep learning techniques over existing machine learning techniques is also stated in terms of data requirements, learning, etc which is the need of the hour as the medical database is ever increasing phenomena demanding faster results. Though these studies are vast, this spectrum of research requires more rigorous investigation in terms of classification with minimal errors. In this paper, a proposed Deep Learning (DL) system is connected on large dataset to assess the prediction on the breast disease mammogram images as compare to state-of-art classification strategy. Despite the fact that this automation is known for its robustness still its execution relies on two key focuses that are: Clustering and Classification. The DL system result shows better qualitative result as compared to Multilayer Perceptron (MLP) method. The best precision of 86% for the given dataset is accomplished through proposed method when compared with different classifiers in terms of accuracy.

Keywords— Breast Cancer, Ultrasound, Mammography, Computer Aided Diagnosis(CAD) , Convolution Neural Network (CNN), Multi-Layer Perceptron(MLP), Machine learning techniques, Accuracy

I. INTRODUCTION

Health related diseases are increasing day-by-day in the world which even causes and increases death rates. Breast malignancy is one of the primary issues which the females are looking all through the world. "The factual information accessible by the World Health Organization (WHO) announced that 23% of growth related cases and 14% of tumor related passing among ladies are happened by breast malignancy [1]".So, keeping in mind the end goal to confine the reason for the breast disease the main tool used is the early stage detection with the help of screening programs [2], "which commonly use mammography for breast imaging". For mammography screening test several steps are included such as the analysis and detection of lesions which might be as masses or calcifications that estimate the risk which is being produced in the patients as a breast cancer. This investigation is clinically demonstrated by the manual framework which is subjective appraisal of a radiologist, bringing about a vast inconstancy in the last estimation. The viability of this manual procedure can be pictured by late forecast that demonstrates manual examination has a "Specificity of 91%" and "Affectability of 84%" [3]. "Then again, the systematic outcomes demonstrated that a moment perception of radiologists or CAD framework can expand the execution of same mammogram [3]". This expands the interest of analysts in the advancement of such frameworks with the expansion in the effect of second perusing of CAD framework [4].

A. Breast Cancer Diagnostic Methods

Breast Cancer images and examination strategies assume significant part in identifying breast growth. Numerous product and various types of machines are engaged with location. A portion of the restorative indicative strategies for breast malignancy are given:

- *Digital mammography*

  Digital mammography Digital Mammography is completely updated by full field advanced mammography (FFDM). Here X-beam film is supplanted by strong state indicator .The strong state identifiers do the X-beam film picture changed over into electrical signs. Signs are utilized to catch the breast inward part and creates exceptional computerized picture. In mammogram test, just a single picture can be taken at once and furthermore just a single side of the breast will be caught. Compression of breast causes covering of tissues and hides certain subtle details. So mammogram now and again doesn't demonstrate the disease tumor. Mammogram is the basic test to detect breast cancer. During the mammogram test, the Iron Radiation that goes into the breast indicates inner parts of the body and furthermore the suspicious locale. It demonstrates tissues of breast and veins. Subsequent to finishing the mammogram test, the outcome will be appeared in X-beam film sheet. These days there are 3 propelled strategies incorporated into mammography [5]. Principle weakness is pressure of breast isn't happy for all women. It may be a painful procedure in Figure 1.

Figure 1: Mammogram

- ***Computer Aided Design (CAD)***

CAD creates carefully procured mammogram. CAD programming assumes real part in this mammography. It recognizes unusual zones of thickness and mass calcification that might be the nearness of growth. Computer aided design is exceptionally useful to radiologist to recognize the growth [5] for location of breast Cancer in Ultrasound Images as in Figure 2.

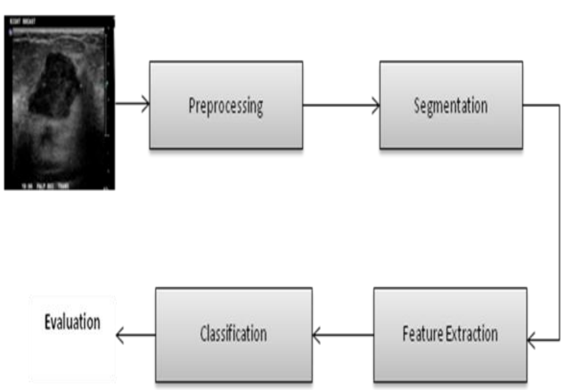


Figure 2: Computer Aided Diagnosis for Ultrasound Images

- *Breast Tomo-synthesis*

It is a 3 dimensional picture representation of breast utilizing X-beams. It isn't considered as standard testing of breast malignancy. Principle downside in this testing is that the device isn't accessible in numerous healing facilities. Breast Tomo-synthesis overcomes the above said disadvantage of mammogram. Breast Tomo-synthesis takes multiple images of breast at many different angles. Breast Tomo-synthesis have x-ray tube arc. During the test, X-ray tube arc around the breast and takes highly clear 3 dimensional images [5].

In previous days researchers collected the real time image from various places and hospitals and it was difficult to collect. Nowadays medical image data are available online, which can be easily fetched and used for research purpose. Some of the breast image databases are mentioned in Table 1.

Table 1: Available Breast Image Sets of biomedical investigation

Database	**Number of images**	**Image capture technique**	**Image type**	**Total patient**
[6] "Radboud University Nijmegen Medical Centre (Nijmegen, The Netherlands)"	104	Mammogram	--------	186
[7] BUS images	--------	MG	DICOM	--------
[8] "Sardjito Hospital Yogyakarta"	30	MR, SEG	BMP	--------
[9] "Mini-MIAS (Mammogram Image Analysis Society)"	322	Mammogram	--------	322
"DDSM (Digital Database for Screening Mammogram)"	2500	Mammogram	--------	--------
[10] "UCI Machine Learning Repository" - "Breast Cancer Wisconsin (Original)" - "Breast Cancer Wisconsin (Prognostic)" -"Breast Cancer Wisconsin (Diagnostic)"	251 699 -------- --------	-------- Digitized Image Digitized Image	-------- -------- --------	341(training) 342(testing) 30(features) -------- --------

B. Comparative Analysis of Machine Learning & Deep Learning

The Machine Learning and Deep Learning are rapidly being used by the researchers in the medical field especially in the detection of breast cancer. Table 2 and Table 3 represents the theoretical analysis and Parametric Analysis results respectively between the two techniques and interpreted that Deep Learning is better as compare to the Machine Learning.

- *Theoretical Difference Analysis*

Table 2: Relative investigation of Machine Learning with Deep Learning

DEEP LEARNING BASED TECHNIQUES	MACHINE LEARNING BASED TECHNIQUES
Neural networks	
At the point when the issue exhibits nonlinear properties, deep systems appear to be computationally more attractive than shallow systems.	For a similar issue, with a specific end goal to get to an indistinguishable level of execution from of a deep network, a shallow network requires many more connections thus being more expensive.
Kernel methods	
Suitable for big datasets	Expensive in practical use
Flexibility	
More flexible i.e., they can be modified in many ways to suit the tasks	Less Flexible
Resource capacity	
Deep convolution neural networks can handle enormous amount of information, the size of which is in millions	For tasks that require great computational and human resource capacity, classic machine learning strategies are not suitable
Linear vs. non linear data	
Linear and nonlinear data can be handled	For the non linear case, machine learning lags in terms of performance

- *Parametric Disparity Analysis*

Table 3: Parametric Analysis of Machine Learning vs. Deep Learning

PARAMETERS	MACHINE LEARNING	DEEP LEARNING
Data Requirements	Small	Large
Hardware Requirements	CPUs	GPUs
Learning	Supervised & Unsupervised	Supervised
Expert Analysis	Required	Not Required
Modularity	Present	Absent
Problem Solving	Modular	End to End
Execution time	Less	More
Interoperability	Supported	Not Supported
Transparency	More	Less
Merits	• Small data set • Modular approach • Reduces complexity	• Large data sets • Complex problem solving • Save Time for Radiologists
Demerits	Complex environment with modern day data sets cannot be handled especially in the field of image mining	Transparency could be an issue in deep learning

Section I contains the introduction of Deep Learning & Machine Learning, Section II contain the related work of both Machine Learning vs. Deep Learning in Breast Cancer Section III include Methodology, Section IV describes results and discussion and Section V concludes research work with future directions).

II. RELATED WORK

"Computer Aided Diagnosis for Cancer Diagnosis in Breast Ultrasound Images" [12] involves classification and segmentation techniques. The Region of Interest (ROI) is recognized by marker controlled watershed change strategy. At that point, the textural and measurable highlights are joined removed by applying wavelet change. The subsequent stage is characterized by various calculations for recognizing ROI is central lesion or normal. A huge statistical data and studies confirmed the impact of breast cancer as the main source of women death worldwide. So, the patient survival rate can increase with the detection and diagnosis of breast cancer by early screening test and advanced treatments options. "A novel breast tumour grouping calculation utilizing neutrosophic score highlights [14] is discovered". A managed include determination strategy is utilized to lessen highlight space. At long last, a Support Vector Machine (SVM) classifier is utilized to demonstrate the segregation power of the proposed highlights set. "The framework is approved by 112 cases (58 malign, 54 benign)". The test comes about demonstrate that such highlight set is promising and 99.1% grouping precision is accomplished. At long last, central sore is delegated benign or malignant. "Support Vector Machine (SVM), K-Nearest Neighbour (KNN) and Classification & Regression Trees (CART) are used to achieve the classification task". "The result proves that in case of classifying between benign and malignant tumor the combined statistical and textural feature extracted is better in CART by 83.75% in terms of classification rate as compare to SVM and KNN". "SVM and CART get 100% grouping rate utilizing texture element if there should be an occurrence of separate amongst ordinary and irregular classes". The picture set comprises of 50 pictures (38 Benign and 12 Malignant) and the edges were thought about against manual exception drawn by radiologist. The assessment parameters i.e. "Accuracy, Sensitivity, Specificity, Matthew's relationship coefficient (MCC)" alongside "receive operating Characteristic (ROC) curve for proposed CAD frameworks has expanded" [18] while a strong arrangement utilizing robotized and division on textural investigation premise is performed on Ultrasound Images [19]. The fundamental issues which make the procedure of division troublesome are poor picture quality (low differentiation, foggy limits, low SNR (signal/noise ratio), etc.), and so forth.), and precisely decreases a ROI which accurately covers the tumor region. The benefits of "Breast Ultrasound System" help in early stage detection of cancer and "large amount of scaling to develop a successful CAD system". The difficulty is solved by a novel approach based on the supervised texture classification. "The benefits of the new technique are firstly it can classify the BUS images without any human intervention and secondly the classification is quite accurate."

In addition, **[20] [21]** Computer Aided Diagnosis of Breast masses utilizing BI-RADS discoveries and in view of Colour Doppler Flow Imaging is utilized for biopsy. A novel breast characterization framework in view of B-Mode ultrasound and shading Doppler stream imaging is designed. SVM classifier with chose highlight vectors is utilized to arrange breast tumor into benign and malignant. The descriptive capacities were in the vicinity of 76% and 82% and the anticipated descriptors were then utilized for tumor characterization. "Utilizing ROC for assessment, the Area under Curve (AUC) of the proposed CAD was marginally superior to anything that of a regular CAD in view of the blend of every single quantitative component (0.96 versus 0.93, $p = 0.18$)". "The fractional AUC value which is more than 90% affectability of the proposed CAD was fundamentally superior to that of the regular CAD (0.90 vs.0.76, $p < 0.05$)". Taking everything into account, the CAD helped investigation with subjective data from radiologists demonstrated a promising outcome for breast tumor order. Other approach is for "BI-RADS breast lesion is sonography discoveries and pathology connection" [25]. Strategies utilized are Sonograms of "186 BI-RADS 4 non-unmistakable breast sores with a known finding were explored reflectively". "The morphologic highlights of all lesions were depicted utilizing BI-RADS vocabulary and the sores were subcategorized into 4A, 4B, and 4C based on the doctor's level of doubt". "Results are of 186 sores, 38.7% were harmful and 61.2% were favourable". "PPVs as per subcategories 4A, 4B, and 4C were 19.5%, 41.5%, and 74.3%, individually".

The performance and optimal cost of Machine Learning algorithms in breast lesion is main motive **[28].** The feature sets consist of visual radiologist's interpretation and computer extracted based. "Then this set is combined by pruning classifier and Adaptive Boosting (Ada-Boost) to increase the performance in terms of ROC curve and increase the cost of pruning fraction by 20%". The guideline is to combine Ada-Boost with specific pruning to accomplish elite without the additional cost of an extra per user for separating strong breast masses by ultrasound". The best outcome utilizing arrangement calculation in breast tumor recognition is utilizing SVM and Ensemble in [29]. The forecast procedure is normally comprises of three sections: "the pre-preparing, the element extraction and choice and the arrangement stages". Different methodology is used in each phase. Experimental results are applied on image set of "106 ultrasound images (51 containing tumour and 55 images clean of tumour) obtained from medical centres in Alexandria, Egypt". "The SVM classifier has been trained on 70% of the data set and tested on the remaining 30%". On the other part, bootstrap technique was utilized on every one of the information alongside bagging ensemble. "The obtained result has demonstrated the prevalence of bagging ensemble classifier over the SVM classifier". Then again in [30] "Breast massed including surface and shape includes in Sonography Images are presented by Classification calculation utilizing another half and half division approach on set calculations". The six highlights ("Eccentricity", "Solidity", "Concession Area-Hull-Rectangular", "Cross-relationship left", Yielding "Area-Mass-Rectangular" and "Cross-connection right") in view of shape, surface and locale qualities of the majority were separated for advance arrangement. At last SVM classifier was used to arrange breast masses. "The characterization comes about demonstrated a general Sensitivity of 90.91%, Accuracy of 95.00%, Specificity of 97.87%, negative prescient estimation of 93.88%, positive prescient estimation of 96.77%, and Matthew's relationship coefficient of 89.71%". The exploratory outcomes proclaim that our proposed technique is really a useful tool for the analysis of the breast growth and can give a moment feeling to a doctor's choice or can be utilized for the drug preparing particularly when combined with different modalities.

The testing part is rather than manual framework to take a shot at Automated System on extensive dataset which spares the season of radiologists for the forecast of breast lesions utilizing Ultrasound and Mammography Images. The examination is utilizing Deep learning procedures for better exactness as contrast with Machine Learning Techniques. Strategies utilized as a part of [7] is division of BUS pictures including high speckle noise, low contrast, blurry boundaries, low signal-to-noise ratio and intensity in homogeneity. "Automated 3D breast ultrasound (ABUS) is a novel mainstream approach as a modifier to mammography for distinguishing malignancies in women with thick breasts [6]". Above all else a "productive de-speckling strategy is connected on the pictures to diminish speckle noise". At that point, another calculation to distinguish limit masses in view of ISO contours is hypo-echoic which is connected. "The resulted about applicants are assessed by a course classifier whose principle classifiers are Random Under-Sampling

Boosting (RUS-Boost) that is acquainted with manage imbalanced datasets". "Each construct classifier is prepared in light of a gathering of highlights like Gabor, LBP, GLCM and different highlights". The execution of the proposed framework was assessed utilizing 104 volumes from "74 patients, including 112 malignant lesions". "The investigation of Free Response Operating Characteristic (FROC) demonstrated that framework accomplished gigantic increment in the Case-based Sensitivity and Region-based Sensitivity".

"Computerized Detection of Breast Cancer Lesions Using Adaptive Thresholding and Morphological Operation" in [8] demonstrates that the proposed strategy effectively accomplished the "Precision of 95.19%, Sensitivity of 84.13% and Specificity of 96.2%". These outcomes demonstrate that the framework can be utilized to help the specialists or operators from radiology group all the more dispassionately in bosom tumor injury discovery. At that point comes the enhanced robotized disease identification in [31] utilizing CAD which incorporates handheld ultrasound (HHUS) and mechanized 3D bosom ultrasound frameworks (ABUS). "Alternative free-reaction ROC examination was utilized to quantify the execution. The outcomes are without CAD, the average area-under-the-curve (AUC) of the readers was 0.77 and fundamentally enhanced with CAD to 0.84 (p = 0.001)". "Sensitivity of all readers enhanced (run 5.2–10.6%) by utilizing CAD however specificity diminished in four out of six readers (extend 1.4– 5.7%)". In [33] Automated Breast Ultrasound (ABUS) is exceedingly compelling as breast growth screening adjunct innovation. "Over a database of 145 volumes, with 36 biopsy confirmed sores, accomplished outcomes demonstrate Area under the Curve (AUC) estimations of 92.6% for lesion location and 89% for lesion characterization".

At that point the following viewpoint was assessment of robotized framework utilizing Colour-coded Acoustic Radiation Force Impulse Imaging (ARFI) [34] and to research the estimation of shading coded Virtual Touch tissue imaging (VTI) in the portrayal of breast lesions and to contrast it and traditional ultrasound (US). "ROC curve for consolidated customary US and VTI (0.945) was altogether higher than that for regular US (0.902) and for VTI (0.871) (p<5, 0.0021 and p>5, 0.001 separately)."

In 2016, Xu's et.al [35] introduced information-pushed data-driven methods combination data from three-D model collections to improve the analysis, modelling and modifying of shapes. Then, an Accurate Method Using Probabilistic Fuzzy Clustering Algorithm in [36] was represented. "The results are as 55 benign and 75 malignant tumour images are collected and analyzed. Probabilistic fuzzy diffusion reduces the error rate to .092 for benign mass and .000034 to malignant one". Table 4 represents the related work of Machine Learning and Deep Learning Techniques in Ultrasound and Mammography breast lesion.

Table 4 Summary of studies on Breast Ultrasound & Mammography Images using Machine Learning & Deep Learning Techniques

AUTHOR AND YEAR	REFERENCE NO.	TECHNIQUES	PARAMETERS	STRENGTHS	LIMITATIONS
Computer Aided Diagnosis Using Classification Algorithm in Ultrasound and Mammography Breast Cancer Images					
"S. K. Alam" (2011 "Bangladesh Journal of Medical Physics")	[13]	"BI-RADS Using Quantitative Features"	"Heterogeneity", "Echogenicity", "Aspect Ratio", "Area", "Shadowing", "Border Irregularity", "Margin"	Provide consistent results	Fibrous, Glandular, and Fatty Breasts haven't been distinguished
"Khalid M. Amin" (2015 Science Direct)	[14]	"SVM", "Neutrosophic" "Similarity Score (NSS) algorithm"	"Diameter" , "Area", "Elongation", "Circulation", "Perimeter" , "Compactness""Eccentricity"	Classification accuracy offered is higher.	Limited dataset
"W. Gomez" (2012 IEEE)	[18]	"Grey Level Co-Occurrence Matrix(GLCM)", "Minimal-Redundancy-Maximal-Relevance(MRMR)", "Fisher Linear Discriminant Analysis (FLDA)"	"Texture Features"	GLCM features give better execution	GLCM statistics combined with other textures features and morphological Features is ignored
"Yan Liu" (2012 Springer)	[20]	"B-Mode ultrasound and shading Doppler stream imaging based Novel breast arrangement", SVM	"Positive predictive value (PPV)", "Negative predictive value (NPV)", "Accuracy", "Sensitivity", "Specificity",	Without visually inspecting we can optimize detection of blood flow indices automatically.	Hybridization of classifiers is ignored
Woo kyung moon (2013 Science Direct)	[21]	Computer-aided analysis with quantitative information	"Shape" , "Orientation" , "Margin", "Echo pattern", "Posterior Feature", "Lesion Boundary"	Partial AUC over 90% sensitivity	Use of all tumors in the feature selection process
"S. Muthuselvan" (2016 ICICES)	[22]	"Random Tree", "One R", "Zero R", "Naive Bayes" and "J48".	"White blood cell", "Red Blood Cell" "Platelet" "Hemoglobin" "Lymphocytes"	J48 algorithm gives the best result.	Hybridization of classifiers

"Chandra M. Sehgal" (2012 IEEE)	[23]	"Naive Bayes" and "Logistic Regression"	"Brightness difference", "Margin sharpness", "Angular variation at margin", "Depth-to-width ratio" , "Axis ratio", "Tortuosity", "Radius variation", "Elliptically normalized skeleton"	Demonstrate reduction in biopsies by 48%	Independent validation can produce more suitable results
"L. Sellami" (2015 IEEE)	[24]	CAD System and SRAD (Speckle Reducing Anisotropic Diffusion) filtering	"Shape" , "Orientation" , "Margin", "Echo pattern", "Posterior feature"	Extract more information about breast cancer lesions	Better result can achieved by using classifiers with texture or morphological features
"Juan Shan" (2015 Science Direct)	[25]	"SVM", "ANN", "Decision Tree", "Student's t-test", "Random Forest"	"Shape", "Orientation" , "Posterior Feature", "Margin", "Echo Pattern"	Better performance of clustered classifiers in a tumor classification task. Best ROC performance	Hybridization of classifiers has been ignored
"Santosh S. Venkatesh" (2015 Science Direct)	[28]	"Machine Learning technique involving Adaptive Boosting and Selective pruning"	"Shape" , "Orientation" , "Margin", "Echo pattern", "Posterior feature"	Enhance the execution of human spectators Computer-based examination to supplement	The number of cases forgot isn't controlled from the earlier, however is acquired from the assertion or contradiction of the classifiers on the sample
"Fahimeh Sadat Zakeri" (2010 Springer)	[30]	"Support vector machine (SVM), crossover division approach in view of level set"	"Eccentricity", "Solidity", "Deference area hull rectangular", "Deference area mass rectangular", "Cross-correlation-left" and "Cross-correlation"	medicine training	Extraction and what's more, assessment of novel features to have better classification results
Deep Learning in Ultrasound and Mammography Breast Cancer Images					
"Ehsan Kozegar" (2017 Elsevier)	[6]	"Automated Breast Ultrasound", "Computer Aided Detection", "Iso-contours Cascade classification"	""Sensitivity, false positive per picture, specificity, F-measure and MCC""	"The accomplishment is as the Region-based Sensitivity and Case-based Sensitivity of 68% and 76% at one false positive for every picture accomplished"	--------

"Muzni Sahar" (2016 "International Conference on Information Technology Systems and Innovation")	[8]	"Ultrasound, detection, Adaptive Thresholding, Morphological"	"Dice coefficient", "Jaccard coefficient", "Hausdorff distance", "Accuracy", "Sensitivity", "Specificity"	Method can be used to automatically detect the breast lesions in ultrasound image.	--------
"Zelst" (2017 Elsevier)	[31]	"Computer Aided Detection Ultrasound, Automated breast ultrasound"	"False positive fraction", "lesion location fraction", "Sensitivity", "Specificity"	Radiologists reading ABUS may benefit from the studied implementation of CAD-software as it increases cancer detection.	study time constraints
"Zishun Liu" (2016 Elsevier)	[32]	"Upright orientation Data-driven shape analysis Voxelization Convolution Networks"	--------	Because of feature learning ability of "Conv-Nets", not only man-made objects but also natural ones can be handled.	First, this approach is not as accurate as geometric methods.
"Arathi Sreekumari" (2016 IEEE)	[33]	"ABUS"	"Intensity", "entropy"	------	-------
"Zhou" (2016 Elsevier)	[34]	"Ultrasound", "Elastography", "Acoustic radiation force impulse"	"Threshold", "Sensitivity", "Specificity", "area under ROC curve value"	Color coded VTI with the proposed four-point scale score system has potential in diagnosing solid breast lesions as malignant or benign.	-------
"Kai Xu" (2017 Computer Graphics forum)	[35]	data-driven approach, machine learning	--------	Survey	-------
"Vidya" (2016 "International Conference on Communication Systems and Networks")	[36]	"Ultrasound", "Adaptive Histogram Equalization", "Probabilistic fuzzy clustering algorithm", "Morphological	MSE, PSNR(db)	Ultra sound imaging methodology has significant advantages over other methods in terms of cost, size and detection resolution. The results reveal that	---------------

		operation”		Hybrid filter is most appropriate to remove speckle noise than Homomorphism filter.	

There are sure requirements that have been ignored in Table 4 about the Machine Learning Techniques which can be overcome by the Deep Learning which is described below:

- For manual system using classification unsupervised learning technique is time consuming to show accuracy on single image of huge dataset.
- The utilization of mechanized deep learning method can be done on immense dataset and to improve the precision rate for breast malignancy identification.

Examination of the current techniques demonstrates that precision rate has ended up being insufficient hence forth advance us required to make them more reliable.

The proposed works focus around to arrange the breast growth region. The identification of breast disease is considered in [11] was unsupervised classification problem using WEKA along with Multilayer Perception (MLP) in manual system whereas proposed work is totally based on supervised problem and can be evaluated utilizing deep learning system. To apply a classification method such as decision tree if there should be an occurrence of picture preparing it is required to separate the given measure of highlights from the information picture yet in proposed work the highlights are removed inbuilt layer of deep learning. In [11] MLP is connected to characterize the exactness rate amongst benign and harmful breast malignancy while proposed work will enhance the precision of breast disease arrangement.

III. METHODOLOGY

The data for the current study is analyzed and studied from “www.peipa.essex.ac.uk/pix/mias” which is the benchmark database known as Mini-MIAS including Mammographic Images Films taken from the Breast Screening Program in the United Kingdom are digitized up to 50 micro pixels edge with the Joyce-Loebl microdensitometer, in device linear each pixel is represented with a 8-bit word and optical density range 0-3.2. The database accommodates 322 digital films and consumed by 2.3GB 8mm (Exabyte) tape. “The database has been reduced to a 200 micron pixel edge and padded so that all the images are 1024x1024 sizes” [9] which includes Normal=208 and Abnormal(Benign & Malignant) =114.

The methodology process is explained step by step as described in Figure 3 including Image Pre-Processing, Feature Extraction with CNN layers and Classification Process.

A. Image pre-processing

Image is the protection of visual confirmation either by previous techniques or advanced strategies. In advanced perspectives, it is the intensity matrix representation. Every component of the matrix speaks to the power estimation of the pixel in the corresponding position. In a gray scale image, the intensity value varies from 0 to 255. 0 indicates black (minimal intensity) and 255 indicates white (maximum intensity), giving a total of 256 = 28 different levels of gray. Image processing cite to digital image. Noise is the inclusion of the image when receiving or transmitting the image. It damages the image quality, which causes more operational problems in future. Noise is a random change in the intensity of the image. This means that pixels in the image display different integral values instead of their true values.

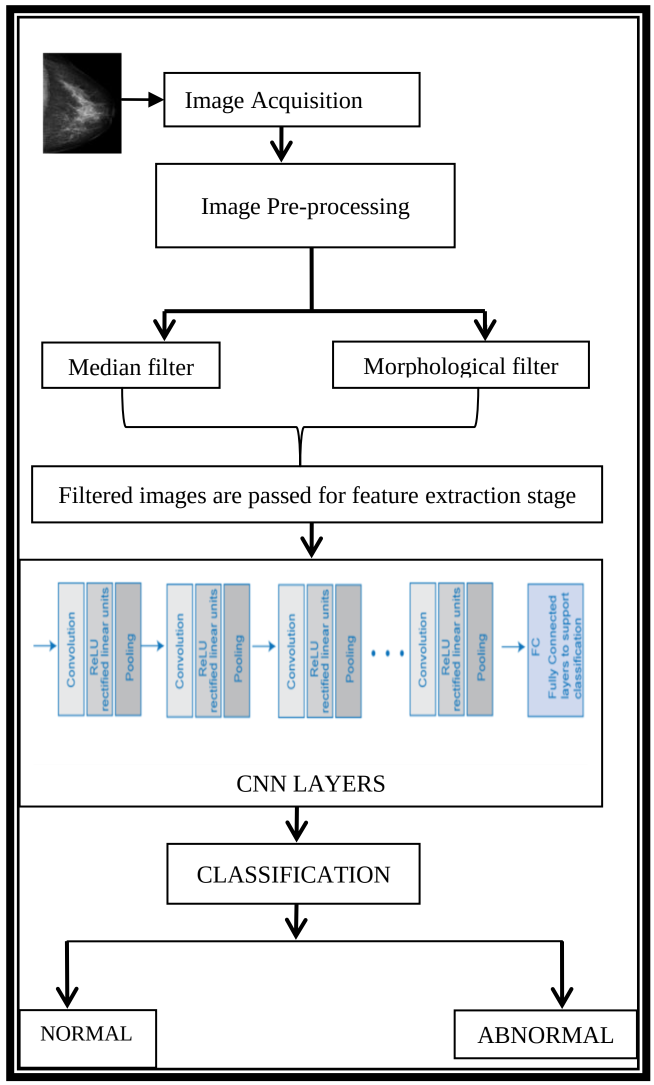


Figure 3: Proposed Methodology

The purpose of the pre -processing is to improve the image aspect that prevents unwanted distortions or improves some image features related to further processing and analysis tasks. Image pre-processing uses the redundancy in images. In image processing, diagnosis of noise and filtering process is very crucial to get the enhanced image quality. Filtering techniques such as median filter and mean filter are very commonly used to restore the corrupted noisy image to the original image. As mammograms take time and effort to interpret, pre-processing will be needed to increase the quality of an image and also make the feature extraction and segmentation stages easier and reliable ones. This stage is normally used for noise-reduction to improve image so that we are able to detect the worrisome features more accurately. This article contains an effective media filter and morphological image processing to enhance image features.

- *Noise*

Speckle noise is a small spot as a natural skin color spot. So, this noise refers to a random generation of many small dots in the image. In ultrasound imaging and SAR this type of noise is there. For better viewing and accurate image analysis, noise quality of original image should be from noise, which is why the concept of de-noising emerges. De-noising is one of an important aspect in image processing. Original image is restored from noisy images by improving the image quality.

- *Filtering methods*

Filtering is often a technique to take off the undesirable information by a perception, in an attempt to allow it to be more appropriate for the next measure in the photo processing. Various types of filtration system are utilized to take off the speckle sounds by images. All of us discuss some special filtration system which is used for de-speckling this image. This different types of filtration system made use of are generally since follows.

Mean Filter: This is a windows dependent linear course filter known as average filter. It is used to eliminate the speckle sounds having a using a sq kernel (i.e. 3x3, 5x5, or perhaps 7x7) with grey-level values. Within typical filtration system, this noisy pixel is definitely supplanted from the signify (average) of your neighbouring pixel values. This filter probably blurs this speckled graphic.

$$I(i, j) = \text{mean}\{x[m, n], (m, n) € w\} \quad (1)$$

Table 5: parameter description

W	Neighborhood
And	location [i, j]

Median filter: Median filter, an effective to distinguish out-of-range isolated noise from image, replaces a corrupted pixel by the median of the all pixels in a neighbourhood.

$$I(i, j) = \text{median}\{x[m, n], (m, n) € w\} \quad (2)$$

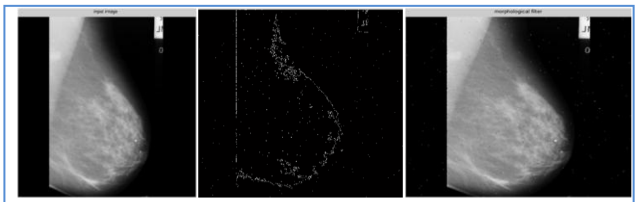
Table 6: parameter description

W	neighborhood
And	location [i, j]

Morphological operation: Morphological tasks are identified with the shape or morphology of highlights in a picture. These activities depend just on the relative requesting of pixel esteems, subsequently, suited for parallel picture preparing, however can likewise be connected to gray scale pictures. Consider a binary image 'B (u, v)' can be computed using a dilation followed by a subtraction:

$$I' = I \ominus H \quad (3)$$

$$B(u, v) = XOR(I'(u, v), I(u, v)) \quad (4)$$



Original Image Morphological Segmentation Morphological Filter Image

Figure 4 Morphological operations

B. *Convolution Neural Networks(CNN)*

"A deep CNN is a classifier that takes an processed image 'x' as input, mostly with multiple channels corresponding to different colours (e.g., RGB) and outputs the conditional probability distribution over the categories 'p(y|x)'". This is obtained by a series of nonlinear functions that gradually transform the input pixel-level image. A major assets of the deep CNN which make it different from a Multi-Layer Perceptron (MLP) [11], is that it heavily relies on "convolution and pooling layers which make the network invariant to local translation of visual features in the input [37]".

- *CNN Layers*

There is a strong reason in building a deep neural network for multi-view data. Most of data lies into one of two parts. "First part consists of unsupervised feature extraction from multiple views along with different classification algorithms [21, 24, and 28]". "They usually train a MLP with unlabeled examples and use the output of such a network as a feature extractor, followed by a standard classifier". In [6], the proposed method builds a multi-view deep convolution network directly for classification. A variant of MLP which was motivated by [11] is the proposed methodology as a novel approach named as MLP-DL. This MLP-DL computes the output in two stages. In the first stage, the output of the processed images (randomly 20 images) out of 322 is passed as a input to the hidden layer of CNN and then internally number of convolution and pooling layers is separately applied to each of the views for feature extraction. We denote such view specific representation by ‘hv’, where v refers to the index of the view. These view-specific representations are concatenated to form a vector, “[hL−CC, hR−CC, hL−MLO, hR−MLO]”, which is an input to the second stage - a fully connected layer followed by a soft max layer producing output distribution “p (y | x)”. The whole network is trained jointly by stochastic gradient descent with back propagation [37].

• *High-Resolution Convolution Neural Network*

It is common in object recognition and detection in natural images to heavily downscale an original high-resolution image. “For instance, the input to the network of the best performer in Image Net Challenge 2015 (classification task) was an image downscaled to 256 × 256”. “This is often done to improve the computational efficiency both in terms of computation and memory and also because no significant improvement has been observed with higher-resolution images”. It betray the inherent property of the natural image in which the objects of interest are represented larger than the other objects, and their macro structures, like the shapes and the other global descriptors., is the most important. “However, downscaling of an input image is not desirable in the case of medical images and in particular for early-stage screening based on breast mammography”. A main objective for diagnosis is a subtle ending which may be achieved only at the original resolution. For computational issues of full resolution images, the system introduced aggressive convolution and pooling layers. “First, convolution layers with strides larger than one in the first two convolution layers is used”. Also, the first pooling layer has a larger stride than the other pooling layers. Then reduce the size of feature maps early in the network. “Although this aggressive convolution and pooling loses some spatial information, the parameters of the network are adjusted to minimize this information loss during training. This is unlike downscaling of the input, which loses information unconditionally”. “Lastly, the average of output vectors from the last feature map instead of concatenating them, which has been a more common practice, is done”. This drastically reduces the dimensionality of the view-specific vector without much, if any, performance degradation as in Figure 5 [37].

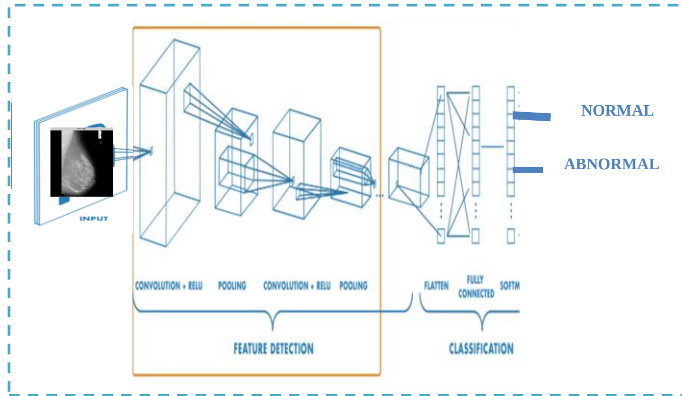


Figure 5: Working of hidden layers of Convolution Neural Network [37]

C. Classification

The output of the Feature Detection is passed to the Fully Connected layer (FC) that outputs a vector of ‘K’ dimensions where ‘K’ is the number of classes that the network which will be able to predict the classification result. This vector contains the probabilities for each class of any image being classified. The final layer of the CNN architecture uses a soft max function to provide the classification output as NORMAL or ABNORMAL.

IV. RESULTS & DISCUSSION

The dataset include Mini-MIAS benchmark database of 322 images with NORMAL (208) cases and ABNORMAL (114) cases. The result of manual system using MLP as well as proposed method using DL is represented in Figure 6.

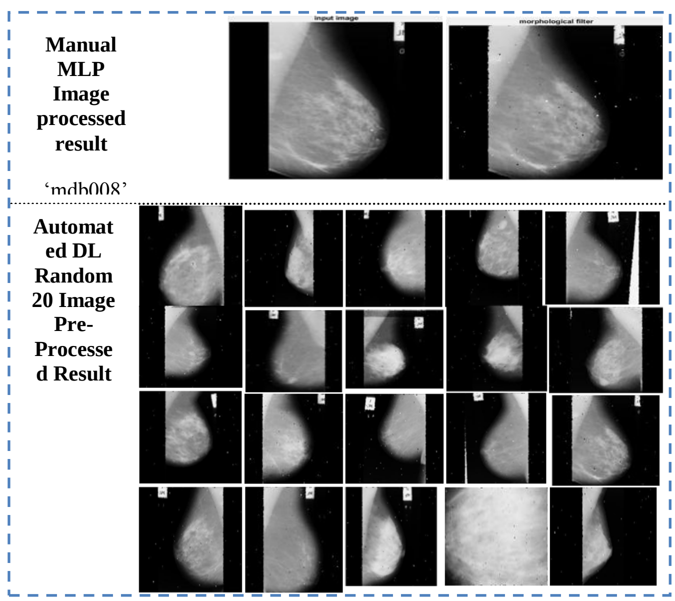


Figure 6: Pre-processed images results of MLP and Proposed Automated DL

The qualitative result predicts that the automated system is much easier, simple and less time consuming in case of huge amount of dataset as compare to Manual system of MLP.

A. Result of Image Pre-Processing Parameter

The various quality metrics which can be used are as follow:

- Signal-to-Noise Ratio(SNR) :

$$SNR= 10 \log 10 \left(\frac{\sigma_g^2}{\sigma_e^2}\right) \quad (5)$$

Where $'\sigma_g^{2}{}'$ is variance of noise-free reference image
$'\sigma_e^{2}{}'$ is variance of error (between the original and denoised image)

- Coefficient of Correlation(CoC):

$$CoC= \frac{\varepsilon(g-\overline{g}).\left(\hat{g}-\overline{\hat{g}}\right)}{\sqrt{\varepsilon\left(\Delta g-\overline{\Delta g}\right)^2.\varepsilon\left(\Delta g-\overline{\Delta\hat{g}}\right)}} \quad (6)$$

Where $\overline{g}$ is mean of original image,
$\overline{\hat{g}}$ is mean of denoised image.

- Edge Preservation Index(EPI):

$$EPI= \frac{\varepsilon\left(\Delta g-\overline{\Delta g}\right).\left(\Delta\hat{g}-\overline{\Delta\hat{g}}\right)}{\sqrt{\varepsilon\left(\Delta g-\overline{\Delta g}\right)^2.\varepsilon\left(\Delta g-\overline{\Delta\hat{g}}\right)}} \quad (7)$$

Where, $'\Delta g'$ is high pass filtered version of 'g' obtained with a 3*3 pixel standard approximation of Laplacian operator $'\overline{\Delta g}'$, '$\overline{\Delta\hat{g}}'$ is mean of original and denoised image.

Table 7: Image Pre-Processed Parametric Result

	PSNR	SNR	CoC	EPI
MLP (1 manual image result)	40.7656	13.6058	0.9984	0.24058
Proposed(20 Random Images Result)	**41.6910**	**14.7662**	**0.9962**	**0.2752**

As the value of PSNR and SNR is increasing, the better is the quality of the image. Range of CoC and EPI lies between 0 to 1. The interpretation of the above parametric result shows that the proposed result is better as compare to base MLP in terms of PSNR and SNR. The CoC is lying near 1 but still EPI yet to achieve.

Table 9: Accuracy Result

Parameter	MLP(Single Image)	Proposed(Random 20 Images)
Accuracy	76	**86**

B. Result of Training with Iteration Parameter

The random 20 images are loaded and then trained with 256*256 sizes by 7*1 arrays with hidden layers of CNN. The different parameter result with i=10 where 'i' is the number of iteration obtained are:

Training on single CPU:

Table 8: Image Normalization Parameters

Epoch	Iteration	Time Elapsed (seconds)	Mini-batch Loss	Mini-batch Accuracy	Base Learning Rate
1	1	7.68	1.6326	48.44%	0.0005
10	10	65.03	7.4730	53.13%	0.0005

In the case of single CPU the time elapsed is 65.03 sec in automated system for large dataset whereas in manual system it is more for single image. The analysis in Table 8 for Mini-Batch accuracy increases as the number of iteration increases. The graphical result in Figure 7 interprets the directly proportion linear relationship between Accuracy and Iteration.

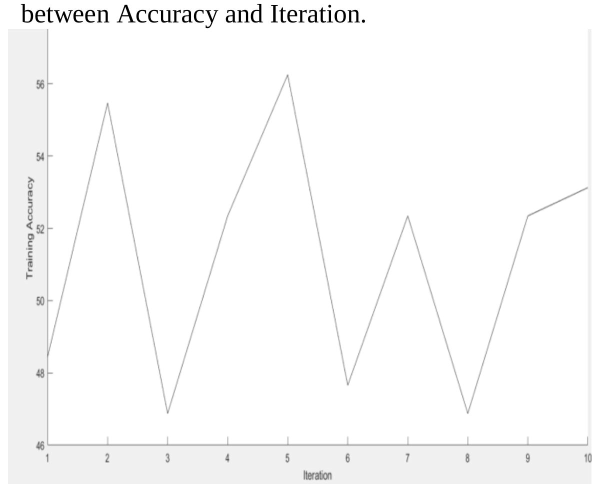


Figure 7: Graphical Result of Training Accuracy with Number of Iteration

- *Result of Accuracy:* Accuracy deals with the effectiveness of the classifier, is most commonly used indicator that reflects precision of results that are predicted and can be computed by following expression.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

The range of accuracy lies between 0 and 100. Accuracy of proposed technique Automated DL is greater than the existing one MLP manual system. Thus, proving that our proposed algorithm provide better result.

V. CONCLUSION

The present review has addressed different deep learning and machine learning techniques which are deployed for breast cancer diagnosis and prediction in literature so far. The automated DL is of random 20 images result as compare to manual single MLP approach. The qualitative perspective is proved by the Deep Learning automated system subjectively by visualizing the results along with the PSNR, SNR, CoC and EPI values. The proposed DL technique achieved 86% accuracy as compare to MLP technique.

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