ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 11, Issue 7, July 2024

Detection and Classification of Breast Cancer using Mammographic Images by Deep Learning

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Abstract: One type of cancer that starts as a cell growth in the breast tissue is called breast cancer. In the US, breast cancer is the most prevalent cancer diagnosed in women, second only to skin cancer. However, breast cancer is not limited to females. Since breast tissue is present in all people from birth, anyone can develop breast cancer. The survival rate of breast cancer has been rising. Additionally, the number of breast cancer deaths is gradually declining. This is largely because funding for research and general support for raising awareness of breast cancer are in place. Medical practitioners can now spot breast cancer early because to advancements in breast cancer screening. The likelihood of a cancer cure increases significantly with early detection of the disease. There are numerous ways to prolong life even in cases where breast cancer cannot be cured. The best treatment options are being selected by medical specialists with the aid of recent advancements in breast cancer research.

Keywords: Landslide monitoring, customized node, Internet of Things, long range radio, LoRa link budget, LoRa sensitivity

I. INTRODUCTION

One of the most prevalent malignancies to strike women and those who identify as female at birth is breast cancer (AFAB). It occurs when malignant cells in your breasts grow into tumors. An invasive breast cancer is one in which the tumor spreads to other parts of the body, accounting for about 80% of cases. Although it usually affects women over 50, breast cancer can also strike women and people with AFAB under 50. Breast cancer is also a possibility for men and those who were designated male at birth (AMAB)

• Infiltrating or invasive ductal carcinoma (IDC): This cancer begins in the milk ducts and progresses to the surrounding breast tissue. In the US, this is the most prevalent kind of breast cancer.

• Lobular breast cancer: This type of breast cancer begins in the breast's lobules, which produce milk, and frequently spreads to the breast tissue that is close by. In the US, it is the second most prevalent

TYPE OF BREAST CANCER : Ductal carcinoma in situ (DCIS): This type of breast cancer begins in the milk ducts, similar to IDC. The distinction is that DCIS stays inside your milk ducts as shown in Fig 1.

LESS COMMON BREAST CANCER TYPES INCLUDE : Triple-negative breast cancer (TNBC): Compared to other breast cancers, TNBC is an aggressive, fast-spreading invasive cancer. Inflammatory breast cancer (IBC): Resembling a rash on your breast, this uncommon but rapidly spreading cancer grows. In the US, IBC is not common. Paget's disease of the breast: This uncommon cancer can resemble a rash and affect the skin around your nipple. Paget's disease of the breast accounts for less than 4% of all cases of breast cancer.

BREAST CANCER SUB TYPES : Receptor cell status is used by medical professionals to categorize breast cancer subtypes. Protein molecules on or on the surface of cells are known as receptors. Certain molecules in your blood, such as hormones like progesterone and estrogen, can be drawn to or attached to by them. Progesterone and estrogen promote the growth of malignant cells. Healthcare professionals can better plan the treatment of breast cancer by knowing whether the malignant cells contain progesterone or estrogen receptors.

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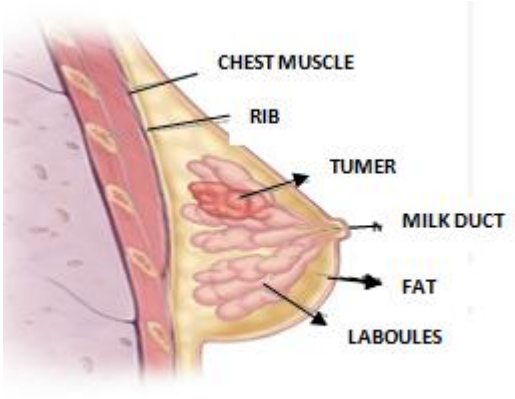

Figure 1. Image detailed various muscles of breast

SUB TYPES INCLUDES

The term "ER-positive" (ER+) refers to breast cancers that carry estrogen receptors. Progesterone receptors are present in breast cancers that are PR-positive (PR+). HR-positive (HR+) breast cancers include progesterone and estrogen receptors. Progesterone or estrogen receptors are absent from breast cancers categorized as HR-negative (HR-).breast cancers that have higher-than-average amounts of the HER2 protein, or those are HER2-positive (HER2+). The development of cancer cells is encouraged by this protein. 15–20% of instances of breast cancer have HER2-positive status.

SYMPTOMS OF BREAST CANCER

Your breasts may be impacted by the illness in many ways. Certain symptoms of breast cancer are highly identifiable. Others can merely appear to be distinct sections of your breast from the rest. Additionally, breast cancer may not show any signs at all. When it does, though, symptoms could include

- A lump or clump that resembles a pea in size.
  • A lump or thickening that stays through your menstrual cycle in your underarms or around your breasts.
  • A variation in the texture or appearance of the skin around your breasts or nipples. Your skin could appear scaly, puckered, dimpled, or irritated. It might appear darker, redder, or purple than other areas of your breast.
  • A firm, marble-like area beneath your skin.
  • A clear or blood-stained fluid leak from the nibble.

Although there are many causes for this illness, specialists believe that breast cancer develops when breast cells change into malignant cells that divide and grow into tumors. They do not know what causes the shift. On the other hand, evidence from study indicates that a number of risk factors could raise your risk of breast cancer. Age Women and people AFAB are far more likely than men and people AMAB to get the disorder if they are 55 years of age or older. Another possible factor is family history; if one's parents, siblings, children, or other close relatives have breast cancer, there is a higher chance that one will get the disease as well. Genetic reasoning: According to research, up to 15% of breast cancer cases are caused by inherited genetic mutations. The BRCA1 and BRCA2 genes are the most often mutated genes. Breast cancer is one of the many cancers for which tobacco usage has been connected. Alcohol-containing beverage use, high obesity, radiation exposure, and hormone replacement therapy can all exacerbate breast cancer.

Stages of breast cancer

Systems for staging cancer are used by medical professionals to plan patient care. Providers can better determine a patient's prognosis—what to expect following treatment—by staging the malignancy. The staging of breast cancer is determined by the kind of breast cancer, the location and size of the tumor, and if the cancer has spread to other parts of the body. The stages of breast cancer are: Stage 0: Your breast ducts are the only areas of your breast where the disease has not spread, indicating that it is noninvasive.

Stage I: Neighboring breast tissue contains malignant cells. Stage II: A tumor or tumors have been produced by the malignant cells. The tumor can be greater than 5 centimeters wide but not larger than 2 centimeters across, or it can be smaller than 2 centimeters across and have migrated to underarm lymph nodes. At this stage, tumors can range in size from 2 to 5 cm in diameter and may or may not impact the lymph nodes in the surrounding area. Stage III: Neighboring tissue and lymph nodes have breast cancer. Locally advanced breast cancer is the term typically used to describe stage Stage IV: Your breast cancer has progressed to other parts of your body, such as your bones, liver, lungs, or brain.

Metastatic breast cancer, or breast cancer that has spread to other parts of your body, including as your brain, bones, liver, and lungs, is the most serious side effect. According to studies, almost one in three women and AFAB individuals

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with early-stage disease go on to develop metastatic breastcancer.

LITRETURE REVIEW AND SIMILAR RESEARCH

Convolutional neural networks (CNNs), one type of deep learning technique, have demonstrated encouraging results in the detection and classification of breast cancer in recent years. In a study that was written up in the Journal of Medical Systems, scientists classified breast cancer in mammography pictures using a CNN. With an accuracy of 91.5%, the suggested system fared better than alternative classification techniques. A CNN was employed in a different study that was published in the Journal of Digital Imaging to categorize breast lesions in ultrasound pictures.

The suggested strategy beat alternative categorization techniques, with an accuracy of 89.2%. A CNN-based method for detecting breast cancer in mammography pictures was presented by researchers in a paper that was published in the International Journal of Computer Assisted Radiology and Surgery. With an accuracy of 92.8%, the suggested methodology outperformed other cutting-edge techniques.

Utilizing gene expression data, a CNN was employed in a different study that was published in the IEEE Journal of Biomedical and Health Informatics to categorize breast cancer subtypes. The accuracy of the suggested approach was 95.5%. Based on gene expression data, researchers employed a CNN in a study published in the Journal of Clinical Oncology to predict the recurrence of breast cancer. With a 71% accuracy rate, the suggested system outperformed other prediction models. A CNN was employed in a different study that was published in the Journal of Digital Imaging to categorize breast cancer based on histological pictures.

With an accuracy of 89.4%, the suggested system fared better than alternative classification techniques. In conclusion, using various types of data, such as mammography images, ultrasound images, gene expression data, and histopathological images, CNNs have demonstrated promising results in the detection and classification of breast cancer. These findings show how deep learning methods may be used to enhance breast cancer detection and therapy. To assess how well these techniques work in therapeutic settings and to address any potential moral or legal concerns that may arise from their use, more research is necessary.

EXISTING MODELLING

Physicians may perform physical examinations or request mammograms in order to look for indications of breast cancer. To identify the illness, however, they do the following tests:

- Breast ultrasound.
- Breast Magnetic Resonance Imaging(MRI) scan.
- Breast biopsy.
- Immmunohistochemistry test to check for hormone receptors.
- Genetic tests to identify mutations that cause breast cancer.

TREATMENT MANAGEMENT PROCESS AND SIDE EFFECTS

The main treatment for breast cancer is surgery, though medical professionals may employ other strategies as well. Breast reconstruction, lumpectomy, and mastectomy are examples of breast cancer surgeries. Surgery may be combined with one or more other treatments, including as targeted therapy, immunotherapy, chemotherapy, radiation therapy, including intraoperative radiation therapy (IORT), hormone therapy, and selective estrogen receptor modulator (SERM) therapy. Common chemotherapy and radiation therapy side effects include fatigue, nausea and vomiting. Targeted therapy, immunotherapy and hormone therapy have similar side effects, including gastrointestinal issues like constipation and diarrhea.

Individuals respond to breast cancer therapy in different ways. Ask your healthcare practitioner about the potential side effects of your therapy, including how they might impact your day-to-day activities, if you are undergoing it. Consult your physician about palliative care as well. In order to make your treatment experience as comfortable as possible, palliative care assists in managing the symptoms of breast cancer and the side effects of the medication.

Breast cancer surgery is not an exception to the rule that all procedures include some risk of complications. It's crucial to keep in mind that surgery can eradicate possibly fatal cancer while you weigh your options. The risks of breast cancer generally exceed the risks of its consequences, which include lymphedema, blood clots that may form after surgery, nerve damage, and surgical site infection.

PROPOSED METHODOLOGY

The block diagram of the proposed system Fig 2 and flow diagram mentioned in Fig 3.suggested technique uses a capsule neural network to identify and categorize different breast cancer types and stages. The convolution layer, primary capsules, and class capsules are the three layers that make up this capsule neural network. There is no loss of spatial information with capsnet, in contrast to convolution neural networks, since it does not employ a max pooling

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Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
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layer.

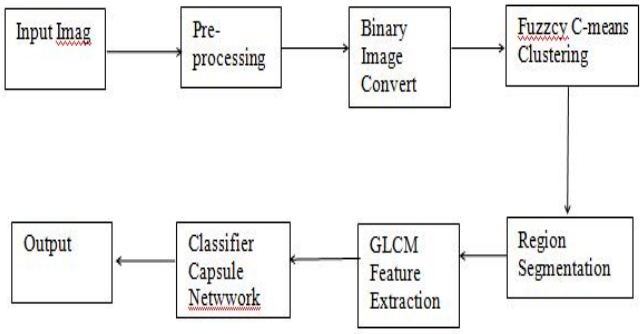

Fig 2. Block diagram of the proposed system

FLOW DIAGRAM OF THE PROPOSED WORK.

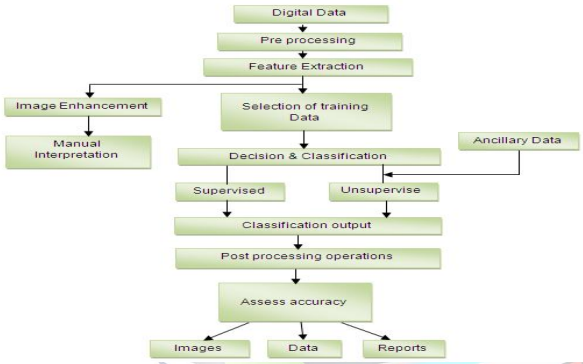

Fig 3. Flow diagram of the proposed work.

1. Pre-processing

Image resampling and enhancement are included in the preprocessing step. The process of altering the amount of pixels in an image is called resampling. A new image with a different width and height in pixels is produced by resampling the original. Up-sampling refers to increasing the size, whereas down-sampling refers to decreasing the size.The resampling process shouldn't result in a change in spatial resolution. The algorithm's performance may be hampered by noise in the input image. On the raw images, image processing techniques are used to improve brightness, contrast, and minimize noise-related artifacts. The input image undergoes an enhancement stage to remove high intensity components, which lessens edge blurring effects and improves smoothness towards piecewise-homogeneous regions. The two techniques used for enhancement are noise reduction and contrast enhancement.

2.Binary Image conversion process

The binarization approach is based on the observation that abnormal mammogram images have a significantly higher proportion of black pixels than white pixels. Therefore, we began counting the black pixels in both normal and abnormal images to obtain an average that could be used as a threshold later on. If the new image's black pixel count exceeds the threshold, it is considered normal; if it is less than the threshold, it is considered abnormal.

The suggested image conversion's functions are as follows:

1) IM2BW - Convert image to binary image via thresholding.

Using RGB, intensity, or index images, IM2BW creates binary images. If the input image is not already an intensity image, it first changes it to grayscale format. Next, it thresholds the grayscale image to convert it to binary. For every pixel in the input image with brightness greater than LEVEL, the output binary image BW has a value of 1 (white), while for every other pixel, it has a value of 0 (black). (Note that regardless of the class of the input image, you specify LEVEL in the range [0,1].

2.BW = IM2BW(I,LEVEL) converts the intensity image I to black and white.

L = BWLABEL(BW,N) yields a matrix L with labels for the connected components in BW that is the same size as BW. N takes two possible values: 4 and 8. 4 indicates 4-connected objects, while 8 indicates 8-connected objects. If the argument is not supplied, the default value is 8. Integer numbers greater than or equal to zero make up the elements of L. The background is made up of the pixels with the number 0 in them. One item is made up of the pixels named 1, another object is made up of the pixels labeled 2, and so on.In BWLABEL(BW,N), [L,NUM] = BWLABEL(BW,N) yields the number of related items in BW in NUM.

Algorithm for Binarization

1. Segmentation is followed by binarization. In this case, binarization is done using the optimal threshold results.

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2. The number of high- and low-intensity pixels is computed following segmentation.
3. The segmented image is made homogeneous so that it is free of malignancies if the high intensity pixels exceed the low intensity pixels.
4. The segmented image is rendered in RGB colors with different colors for distinct connected segments if the high intensity pixels are smaller than the low intensity pixels. This way, the final image depicts areas that are more likely to develop cancer Show the image that was produced.

3.Fuzzy C-Means based Image clustering technique
Multidimensional data can be clustered using fuzzy logic principles, which assign a membership percentage of 0 to 100% to each point in each cluster center. When compared to conventional hard-threshold clustering, which assigns each point a precise label, this can be quite effective. The way this technique operates is by using the distance between the cluster center and the data point to determine membership for each data point that corresponds to that cluster center. The closer the data is to the cluster center, the more affiliated it is with that specific cluster center. It is obvious that the total membership of all the data points should equal one.
A degree of cluster membership was taken in order to segment images using fuzzy C-Means. It permits grouping of a single object that is a part of two or more clusters. As a result, an object may be more prevalent on an edge of a cluster than in its center.

The minimization is done based on

$$= \sum \; i=1 \sum \; i=1 \quad \| \; - \; \|^2$$

In this scenario, m is a real number less than 1, cj is the cluster's d-dimension center, uij is xi's degree of membership in cluster j, xi is the ith of the measured data in d-dimension, and ‖∗ ‖ is the norm of both the measured data and the center. Let V= {v1, v2,….., vc} be the set of centers and X={x1,x2,…..,xn} be the set of data points.

Steps in Fuzzy C-Means

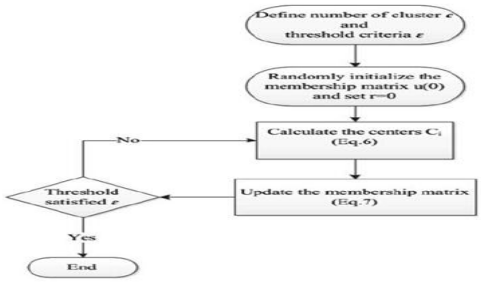

Fig 4. Flow Chart of the proposed work.
The Fig 4 indicates,
Below is a list of the fuzzy c-means process flow:
1. Assume that there are k fixed clusters.
2. Initialization: Determine the chance that each data point xi belongs to a particular cluster k, P(point xi has label k|xi, k), by randomly initializing the k-means μk associated with the clusters.
3. Iteration: Given the probability of membership of each data point (xi), recalculate the cluster centroid as the weighted centroid:
4. Termination: Continue iterating until it reaches convergence or a user-specified number of iterations (it may become stuck at a local maximum or minimum).

$$\mu_k(n+1) = \frac{\sum_{x_i \epsilon k} x_i * P(\mu_k|x_i)^b}{\sum_{x_i \epsilon k} P(\mu_k|x_i)^b}$$

4. Segmenting Methods
Techniques for segmentation can be classified as contextual or non-contextual. The latter group pixels together based on some global attribute, such as color or grey level, but ignore the spatial relationships between features in an image. Contextual methods also take use of these connections; for example, they cluster pixels with comparable grey levels and nearby spatial positions.

GRAY LEVEL COOCCURENECE MATRIX (GLCM):
The spatial association between pixel values in an image is statistically represented by the Gray Level Co-occurrence Matrix (GLCM). Texture analysis is a typical application of it in image processing and computer vision applications. The original image is first converted to grayscale in order to begin the GLCM analysis. By focusing solely on the

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intensity values and avoiding color information, this conversion helps to streamline the study.
The co-occurrence of pixel values within a specified neighborhood around each pixel is determined by GLCM. The pixel relationships that will be taken into account in the GLCM are defined by the neighborhood. A neighborhood window with a square shape is typically utilized, though it can be modified to meet the needs of the particular investigation. GLCM determines the frequency of pairs of pixel values that occur inside the designated neighborhood for each pixel in the image. We refer to these sets of pixels as "co-occurring" pairs. The frequency of a certain co-occurring pixel pair is represented by each element in the square matrix that is the GLCM.

CAPSULE NEURAL NETWORK CLASSIFIER:

An artificial neural network (ANN) called a capsule neural network (CapsNet) is a deep learning system that can be used to more accurately describe hierarchical relationships. This method is an attempt to imitate the structure of the brain as it exists in biology. Neural layers are layered within capsules. Adding layers to a conventional neural network is an ongoing process. You would connect multiple layers inside of one layer in a capsule network. A capsule is a collection of neurons whose activity vector symbolizes the instantiation of quantifiable properties or elements of a certain kind of thing, such an item or a component of an object.
The chance that the entity existing is indicated by the activity vector's length, and the instantiation parameters are represented by the vector's orientation. Using transformation matrices, active capsules at one level predict or divinate the instantiation parameters of capsules at higher levels. When more than one prediction is correct, a higher level capsule activates immediately. "A lower-level capsule prefers to send its output to higher level capsules whose activity vectors have a huge scalar product with the prediction expected from the lower-level capsule." This is the frequent iterative routing-by-agreement technique we employ to arrive at these answers.

SHAPE AND TEXTURE BASED FEATURES ARE THE BASIS FOR MASS DETECTION IN MAMMOGRAPHY. The following is a list of features and output mentioned in Fig 5:

1.Mass area: A = |R|, where R is the set of pixels inside the mass region and |.| is a set cardinal. This is the mass area.

2. Mass perimeter length: The entire length of the mass edge is the perimeter length P. By first determining the mass's boundary and counting the number of pixels surrounding it, the mass perimeter length was calculated.

3. Compactness: C = P2 4_A, where P and A stand for the mass perimeter and area, respectively, is a measure of contour complexity vs contained area. The compactness of a mass with a rough contour is higher than that of a mass with a smooth border.
4.Normalized radial length: This is the total of the Euclidean distances, normalized by dividing by the maximum radial length, between the mass center and each of the border coordinates.
5. minimal and maximum axes: The minimal axis of a mass is the shortest distance that passes through the mass's center from one point on the border to another. The longest path between two points on the border that passes through the mass's center is known as the maximal axis of the mass.
6.Mean roughness of the boundary.

7. Normalized radial length mean and standard deviation.

8. Eccentricity: An area of interest's eccentricity indicates how long it is. A ROI with an eccentricity near 1 resembles a circle, whereas values near zero indicate more stretched ROIs.

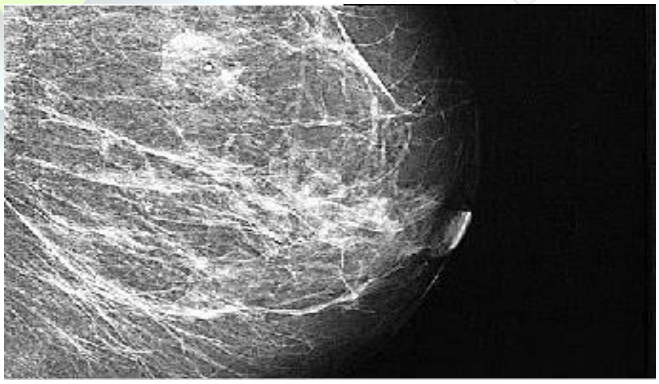

Fig 5. Output Image of the proposed work.

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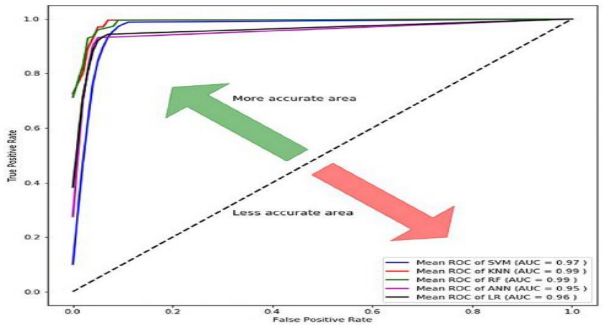

Fig 6. Output representation of the proposed work.

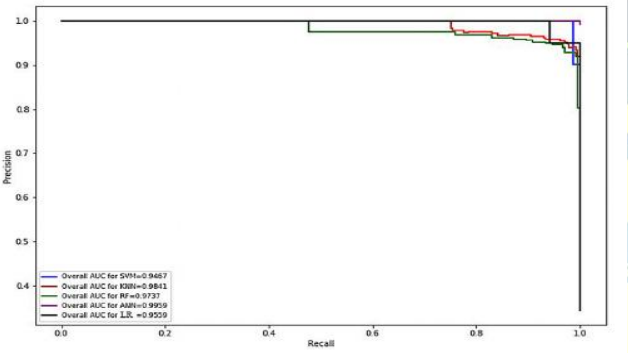

Fig 7. Sharpened Output representation of the proposed work.

Sharpened image

The image that is obtained after image sharpening as shown in figure 6 and 7 is used forsegmentation purpose

RESULTS

A total of 6775 mammography pictures were used in this investigation, of which 976 were used for testing and 5749 for training tabulated in table 1 . The photos come from the Curated Breast Imaging Subset DDSM and the MIAS database. Capsule neural networks were used for training, testing, and classification of these photos. Numerous indicators, including Contrast Correlation, Energy Homogeneity, 36 Mean, Standard Deviation, Entropy, RMS, Variance, Smoothness, Kurtosis, and Skewness, provide an explanation of the condition.

Description	SVM	K.NN	RF	ANN	LR
Accuracy	97.14	97.14	95.71	98.57	95.71
in %					
Sensitivity in %	100	97.82	95.65	100	95.74
Specificity in %	92.3	95.83	95.83	96	95.65
Precision in %	95.65	0.9782	0.9777	0.9782	0.9782
NPV in %	100	95.83	92	100	9.66
FPR in %	7.69	4.16	4.16	4	4.34
FNR in %	0	2.17	4.34	0	4.25
F1 Score	0.9777	0.9782	0.967	0.989	0.9697
MCC	0.9396	0.9365	0.9062	0.969	0.9043

Table 1 Output data collected from the proposed Research

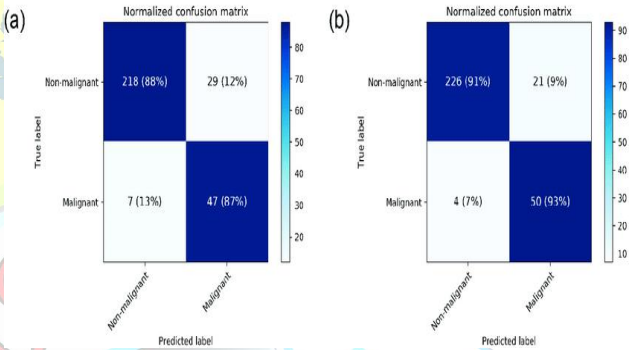

Fig 8. Confusion Matrix of the proposed work.

confusion matrix for breast cancer detection by the best performing (a) DenseNet-169 and (b) EfficientNet-B5.

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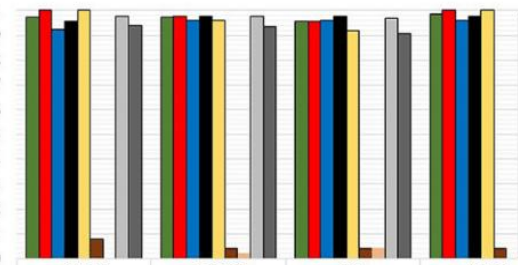

	SVM	K-NN	RF	ANN
Accuracy	0.9714	0.9714	0.9571	0.9857
Sensitivity	1	0.9782	0.9565	1
Specificity	0.923	0.9583	0.9583	0.96
Precision	0.9565	0.9782	0.9777	0.9782
NPV	1	0.9583	0.92	1
FPR	0.0769	0.0416	0.0416	0.04
FNR	0	0.0217	0.0434	0
F1 Score	0.9777	0.9782	0.967	0.989
MCC	0.9396	0.9365	0.9062	0.969

Fig 9. Results and graph Confusion Matrix of the proposed work.

Results Fig 9 of the Confusion matrix of the proposed research have mentioned in the above diagram for end analysis. In conclusion, there has been a lot of promise in the application of capsule neural networks, or CapsNets, for breast cancer detection in recent years. Because CapsNets can record spatial correlations between various elements in the data, they are a good choice for image identification applications like mammography analysis. Studies have shown that CapsNets outperform conventional machine learning techniques in detecting breast cancer with high accuracy rates. It has also been demonstrated that CapsNets are resilient to noise and changes in mammography pictures, which is essential for accurate diagnosis as mentioned in all figures at 10.

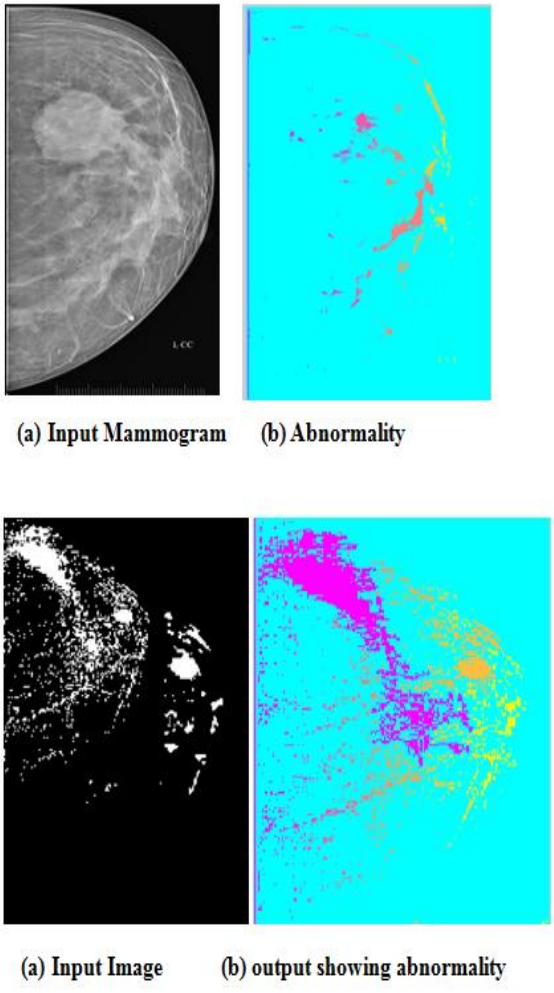

Fig 10 Results Finalof the proposed work.

A mammography is devoid of cancerous tissues if it produces a uniform color image; if not, the abnormality is indicated by the cancerous tissue being represented in cyan. Our preference for a particular hue should be reflected in the code. This is the most often utilized detection technique, and it is really easy to use and effective.

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