A Sisters Similarity Neural Network SSNN Model for Generalization and Detection of Mammographic Breast Cancer Lesion Abnormalities

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Abstract: Breast cancer remains one of the leading causes of mortality among women worldwide. Early detection through mammography significantly enhances survival rates, particularly when abnormalities are identified before metastasis. However, challenges such as tissue density, image noise, variability across mammogram devices hinder consistent diagnosis. The study proposes a robust deep learning framework to automate the detection classification of Breast abnormalities- specifically masses and calcifications. In this research a patch based preprocessing pipeline, involving articraft removal, thresholding, contrast enhancement and dynamic patch extraction resulting high quality and diverse dataset to create thousands of patches. A Novel deep Neural architecture the sisters neural network inspired by Sisters NN is designed to learn discriminative similarity features between image pairs. This approach enhances generalization performance, particular under limited data and high intraclass variability. The network achieves a validation accuracy and testing accuracy of 86.01%, with notable AUC of 0.936. The frame work has integrated an advanced model that allows to predict the unknown lesion in a unseen full scan with mAP of 0.70 and IoU of 84.5%. Additionally, segmentation is done in an enhanced way by Fuzzy c-means and Distance Transform FCDT method which has improved clustering accuracy and lesion localization even in very noisy images or ambiguous tissue regions. The Proposed model demonstrates a superior generalization performance with an accuracy of 92.3%, outperforming with existing models on mAP and AUC metrics. The Framework proposed established a foundation for scalable, best early breast cancer diagnostic tool for generalization.

Keywords: Early Breast cancer detection, Mammogram Abnormality, Mass and calcification lesions, Tissue segmentation, Twin Neural Network, Mammo patch learning, Few Shot learning,· Explainable AI (XAI),·Mammogram Processing, Localization, Fuzzy C Means, Distance Transform, Traditional Federated Learning, Real Time detection support system.

1. INTRODUCTION

Breast cancer remains a leading cause of morality among women worldwide. According to the world Health Organization 2020 approx. 2.3 million women were diagnosed with breast cancer. Approx 6 lakhs deaths were reported globally [1]. India projected 2.5 Lakhs new cases by 2024 and approx. 98% death in the country. Early Detection plays a critical role in improving treatment outcomes, as cancers identified before significant growth or metastasis are more manageable. The American Cancer Society highlights that breast cancer diagnosed at a localized or early stage has an impressive 5-year survival rate of 99% [2]. Regular Screening with mammogram is affordable and is a corner stone for early breast cancer detection.

Mammography employs low dose X Rays tailored for breast cancer imaging, using compression to achieve high quality images with minimal radiation exposure [2]. Typically, the two views in which mammograms are captured are craniocaudal CC View and mediolateral oblique MLO View with the latter being particularly as it reveals more of the upper outer breast quadrant [3]. While mammograms remain the standard irrespective of the cancer severity, breast MRI [4] is occasionally used for high-risk cases but can yield positives.

Interpreting Mammograms can be time consuming and challenging, due to noise, artifacts and complex breast tissue structures [5]. These challenges are further exacerbated by a shortage of skilled radiologists, particularly in under resourced regions [6]. Timely diagnosis and treatment are essential, yet Mammography is not infallible to false Negatives that can delay intervention. To Assist radiologists, the breast cancer Computer aided Diagnosis CADM have been developed as a second opinion tool.

Medical imaging technologies, including mammography, Ultrasound [7, 8], MRI and optical imaging are the pivotal in breast cancer detection [9, 10]. The integration of Artificial AI,Particularyly deep

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learning models, has transformed CAD systems by enabling automatic feature extraction, multi scale lesion detection and improved diagnostic accuracy [11-13].

In this study Digital Imaging and communication in Medicine images provide superior pixel quality and rich metadata which will benefit for deep learning models for preserving critical diagnostic information [14, 15]. Preprocessing remains a crucial step involving articraft removal, thresholding, contrast enhancement, normalization and filtering to enhance image quality and supress noise, thereby facilitating accurate interpretation [6, 16]. However, mammography's sensitivity is limited in women with dense breast tissue, where tumors, lesions, and dense tissue both appear white, making tumors harder to detect [2, 17]. Improving image contrast through methods like CLAHE [18] is essential.

The Key research gap lies in the limited generalizability and robustness of existing Siamese neural network -based approaches for mammogram analysis. While these have shown promise in patch level similarity learning, most existing models rely heavily on manual ROI extraction, patch sampling or lack scalability to full mammogram analysis. Moreover, many studies do not adequately address overfitting, unbalanced data or external validation like factors critical for clinical adaption.

In this work, we introduce a Sisters Similarity Neural Network (SSNN) framework for automated abnormality detection and segmentation [19] in mammograms. Unlike conventional SNNs, the proposed SSNN incorporate twin branch featuring learning with additional contextual encoding, enabling end to end detection without manual ROI. This approach eliminates significantly expediting the diagnostic process while improving robustness across heterogenous datasets. The Proposed system involves in preprocessing steps Artifact Removal, thresholding to minimize cross entropy between foreground and background, contrast enhancement, normalization, filtering. To addresses imbalance and overfitting issues, advanced augmentation strategies are employed and external datasets are incorporated for evaluation [20]. Finally, the SSNN is deployed for accurate and efficient breast cancer abnormality detection, providing a clinically interpretable framework for CAD.

2. MOTIVATION OF RESEARCH

The variation in mammogram instruments and scanning formats presents a challenge for early detection of breast cancer. To address this, we aim to develop a novel method that improve cancer detection accuracy across diverse formats using patch training and model generalization.

- Improve diagnostic accuracy to overcome inconsistencies in mammogram formats to early detection and save lives.
- Enhance generalization to develop models that perform reliable across different devices and formats.
- Increase Adaptability to use patch-based training to make models more sensitive to small, localized features.
- Ensure scalability to make AI tools across various mammogram technologies enabling global use and deployment.

The research aims to create robust, adaptable models that ensure accurate breast cancer abnormalities no matter the equipment which benefits the worldwide.

3. RELATED WORKS

Breast cancer remains one of the leading causes of cancer related deaths among women. Early detection through mammography [21] plays a curial role in improving survival rates and treatments. Deep learning [22] has a significant advanced mammogram analysis by automating [23] tasks like classification, generalization, detection and segmentation. Recent models include CNNs, multitasking learning frameworks and advanced architectures which is giving enhanced accuracy and efficiency.

This paper concentrates on key developments across classification methods, lesion segmentation, object detection and many methods. They are discussed and listed below Table **2**.

Early mammogram classification research primarily used ROI based methods [24] focussing on suspicious lesions with limited context. Arévalo *et al.* [25] leveraged CNNs on selected regions of interest to improve the localized feature extraction. Dhungel *et al*. [26] applied deep belief network to mammogram patches, demonstrating robust patch level abnormality identification. Whole image CNN models given by Akselrod Ballin *et al.* [27], expanded context by incorporating the entire mammogram and patient metadata, enhancing the risk assessment. Shen *et al*.

[28] introduced multi view mammogram classification integrating different views to improve diagnostic accuracy. Lotter *et al*. [29] trained end to end models on thousands of mammograms, boosting generalizability and clinical relevance. Complementary approaches by Dembrower *et al*. [30] and Yala *et al*. [31] developed risk prediction model using longitudinal mammogram data, supporting early detection through temporal changes. Wu *et al*. [32] employed deep multi-instance to aggregate patch level features across whole images bridging local and global information.

Precise lesion and tissue segmentation is critical for clinical decisions. Ribli *et al*. [33] combine UNet and FRCNN architectures to achieve effective lesion segmentation alongside detection. Al-anatari *et al*. [34] demonstrated UNET capability for mass segmentation despite noisy mammograms. Shen *et al*. [35] enhanced segmentation by integrating attention UNET, Focussing on relevant regions and supressing background noise. Dhungel *et al.* [36] combined structured learning with deep features for improving spatial consistency in mass segmentation. Zhang *et al*. [37] applied Deeplab V3 with convolutions for better context aggregation, advancing breast tumor segmentation performance.

Detection methods localize lesions, often via bounding box regression. Ribli *et al*. [33] pioneered using FrRCNN for mammogram lesion detection, a powerful two stage framework. Lotter *et al.* [29] integrated detection in ensemble classification methods to improve sensitivity. Agarwal *et al.* [38] proposed a YOLO based single stage detector for real time lesion detection. Shen *et al.* [39] introduced transformer-based object detectors using attention mechanisms to enhance localization. Choukroun *et al.* [40] applied RetinaNet with focal loss to detect masses and calcifications, addressing class imbalance and achieving state of the art results.

Multi task learning addresses the intertwined nature of mammogram analysis tasks. Macias *et al*. [41] designed attention based MTL models that jointly localize and classify abnormalities, improving efficiency and accuracy. Jiang *et al*. [42] combined BI RADS Classification and mass Segmentation in end-to-end pipelines, yielding better diagnostic outcomes. Lei *et al*. [43] developed joint learning frameworks for ROI classification and localization, exploiting shared representations. Li *et al*. [44] proposed hybrid MTL architectures with task specific decoders to balance shared and unique features. Shen *et al*. [35] combined segmentation and classification using attention modules, highlighting complementary task benefits.

Attention mechanism and transformers capture long range dependencies, revolutionizing medical image analysis. Wang *et al*. [45] applied vision transformers for mass classification showing strong performance despite limited data. Zhou *et al*. [46] used swin Transformers for ROI Classification with hierarchical feature extraction and shifted windows. Shen *et al*. [39] introduced transformer-based detection model with self-attention for improved localization. Zhang *et al*. [47] developed dual branch model integrating multiple mammogram views. Yao *et al*. [48] applied transformer encoder decoder architecture for precise segmentation. Shen *et al*. [35] further combined attention UNet architecture for bridging CNNs and transformers.

In conclusion while significant strides have been made in using deep learning for breast cancer abnormalities classification, detection and segmentation. The gap observed and created an opportunity to further enhance model robustness and generalization. Incorporating advanced architectures like Twin NNs, Inception models with hyperparameter tuning with effective augmentation and cross dataset validation which can push boundaries of automatic diagnosis of breast cancer abnormalities.

4. MAMMOGRAM ANALYSIS AND METHODOLOGY

The CBIS -DDSM dataset is a Curated subset of the original DDSM, designed to facilitate the development of computer aided detection and diagnosis system for breast cancer screening. It contains high resolution mammogram images in 8-bit grayscale TIFF format, typically around 3000 X 4000 pixels for full scans as shown in Figure **1**.

The CBIS DDSM dataset is widely recognized bench mark in breast cancer research, providing annotated mammography images to facilitate the development of detection and classification algorithms [49]. This study utilized the data to analyse the distribution of breast mass and calcification assessments aiding a support in constructing a robust model for analysis.

The breast mass and calcification assessment data is categorized into 6 classes coded with colour from 0 to 5. As shown in Figure **2** Classes 0 and 1 represent low risk, 2 and 3 indicate medium risk, while 4 and 5 correspond to high risk which is aligns with the clinical requirements of prioritizing suspicious lesion.

In this work to improve detection and classification accuracy, we have introduced sophisticated neural

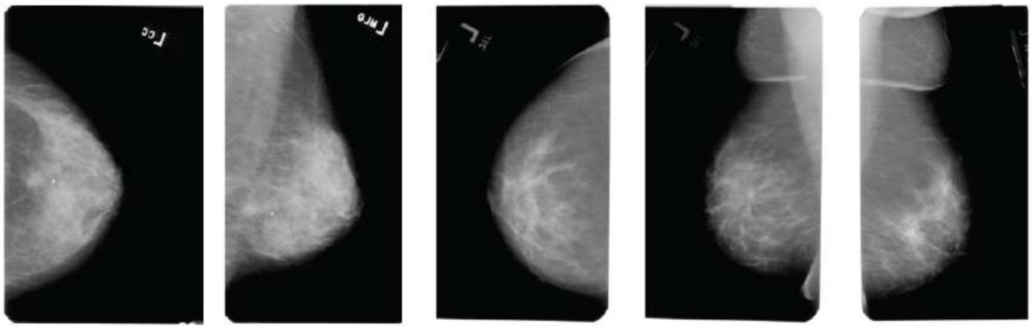


Figure 1: CBIS_DDSM high-resolution mammogram full scan images.

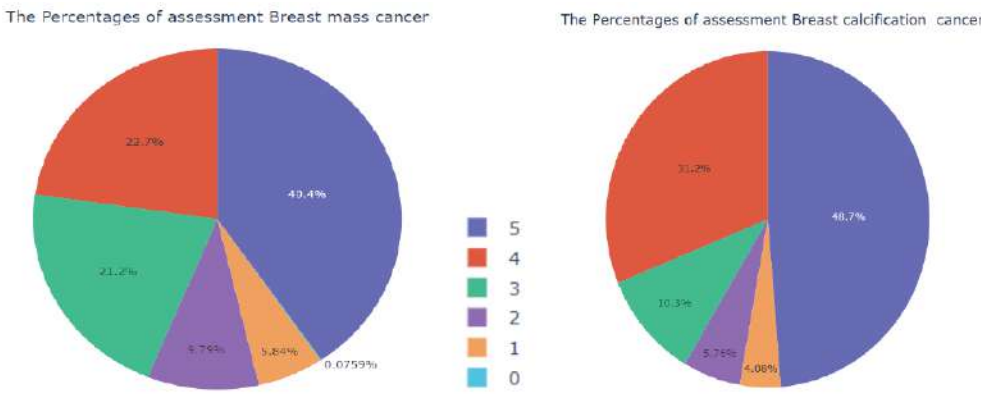


Figure 2: CBIS_DDSM Mass and Calcification Percentages of assessments and their BiRADS Score.

network architectures. Sisters Neural Network or Siamese neural network have gained popularity for medical image similarity assessment, enabling robust feature extraction for classification task [49]. SNNs are particularly effective in handling few shot learning scenarios, which are valuable when dealing with rare classes in breast cancer datasets.

In this work, to improve detection and classification accuracy we have introduced sophisticated neural network architectures. Sisters similarity neural networks SSNNs have gained popularity for image similarity assessment enabling robust feature extraction for classification tasks .Unlike conventional Siamese neural network which primarily focus on pairwise similarity ,the proposed SSNN incorporates contextual encoding and parallel twin branch learning, allowing it to capture both local lesion level features and global breast tissue structures .this makes SSNN particularly effective in handling few shot learning scenarios ,which are valuable when dealing with rare classes in breast cancer datasets. The Inception network architecture has also been applied for breast cancer analysis. The inception module allowed the model to capture multi scale features by employing different convolution filters in parallel, significantly enhancing performance in complex tasks lesion detection and classification [49].

To establish the novelty of the proposed SSNN, it is explicitly compared against baseline architectures: (i) traditional CNNs that often struggle with limited feature discrimination, (ii) Inception based models emphasize multi scale feature extraction but lack similarity driven learning and (iii) conventional SNNs require manual ROI extraction and have limited generalizability. By contrast, the SSNN integrates the strengths of similarity learning with enhanced contextual awareness, enabling end to end automated mammogram analysis.

With this proposed SSNN and Inception hybrid framework is able to classify and generalize the samples effectively paving the way for powerful diagnostic systems. The combined methodology grounded in the CBIS DDSM dataset [50] demonstrates improved sensitivity and robustness, thereby offering a more clinically relevant decision support system for radiologists.

5. MAMMOGRAM PROCESSING AND EXTRACTION OF ABNORMAL PATCHES

To construct an effective dataset for deep learning [51], a structured approach was implemented on full resolution mammograms images and their corresponding ground truth masks. Each Mask served to localize the region of interest ROI as in equation 2. enabling accurate for lesion segmentation [52].

Prior to patch extraction, artifact removal was performed to eliminate labels, markers and background noise using morphological filtering with equation 5 & 6 and component analysis [53]. To further enhance breast region segmentation. Otsu thresholding method [54] was applied to automatically separate the breast tissue from the background based on intensity variance with an equation 2 & 4. For Cases with non-uniform illumination, adaptive thresholding is also utilized as with equation 3. The resulting ROI are extracted as illustrated in Figure **3**.

$$M = \{M_1, M_2, M_3, M_4, M_5, M_6, M_7 \quad M_i \ldots\ldots M_n\} \quad (1)$$

$$\sigma_w^{2(t)} = \omega_{0(t)}\sigma_0^{2(t)} + \omega_{1(t)}\sigma_1^{2(t)} \quad (2)$$

$$M_k = \arg(\min_t \sigma_w^{2(t)}) \quad (3)$$

$$M'(i,j) = \mu_L + \frac{\{\sigma_L^2\}}{\{\sigma_l^2\}}(I(i,j) - \mu_L) \quad (4)$$

$$(M \ominus B)(x,y) = \min_{\{(s,t)\in B\}} M(x+s, y+t) \quad (5)$$

$$(M \oplus B)(x,y) = \max_{\{(s,t)\in B\}} M(x-s, y-t) \quad (6)$$

If the ROI dimensions were smaller than 512-pixel threshold, a dynamic padding was applied to ensure sufficient contextual coverage, following recommended practices for robust patch generation in medical imaging [55].

To improve dataset diversity and mitigate overfitting, random horizontal and vertical flipping augmentation were incorporated during extracting Mammogram patches [56]. From each localized ROI, three random patches of size 256 X 256 pixels were cropped and saved along with their corresponding classes labels and file names for traceability.

From a total 1,200 cases from the CBIS DDSM Dataset [57] 3,582 high quality patches were generated, achieving a label mapping success rate of 97.5%. A small fraction of cases discarded due to missing labels or incomplete image files.

This extraction strategy ensures the construction of a diverse and contextually rich dataset, optimized for training and validating deep learning models in mammographic image analysis [58]. By systematically leveraging spatial localization, image preprocessing, augmentation and careful patch selection, the resulting dataset is well suited for advancing automated breast cancer detection system.

Steps for Extracting Mammogram Patches for Training and Testing

1. List all lesion mask
2. For each mask
   - Load the corresponding image (handle multiple filename styles)
   - Convert the image to numpy array
   - Determine centre and size of the mask (ROI)
   - If ROI is small crop with extra padding, If large crop with minimal padding
   - Randomly apply horizontal /vertical flips the ROI
   - Random crop three patches from the ROI
   - Save patches with labels, filenames for traceability
3. Store the all images and return the collected arrays

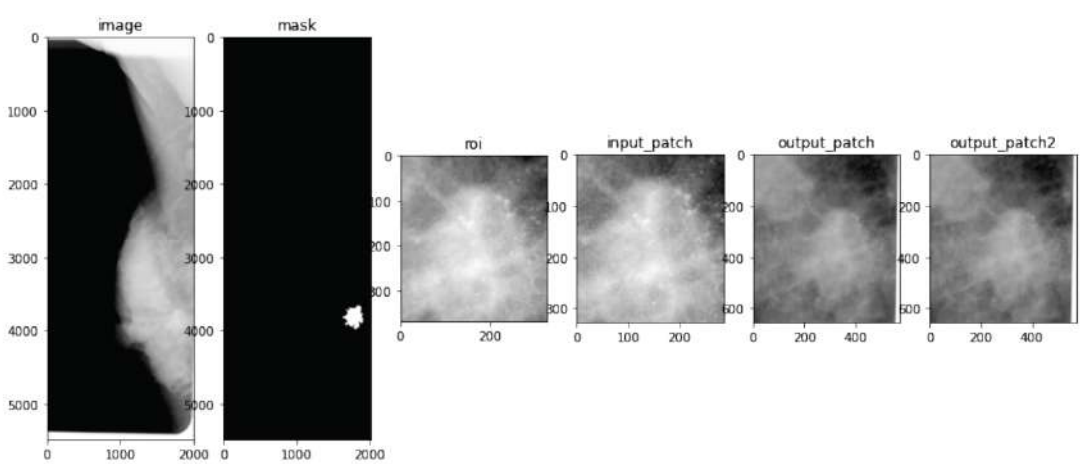


Figure 3: Extraction pipeline Full mammogram; ROI localization; Patch generation.

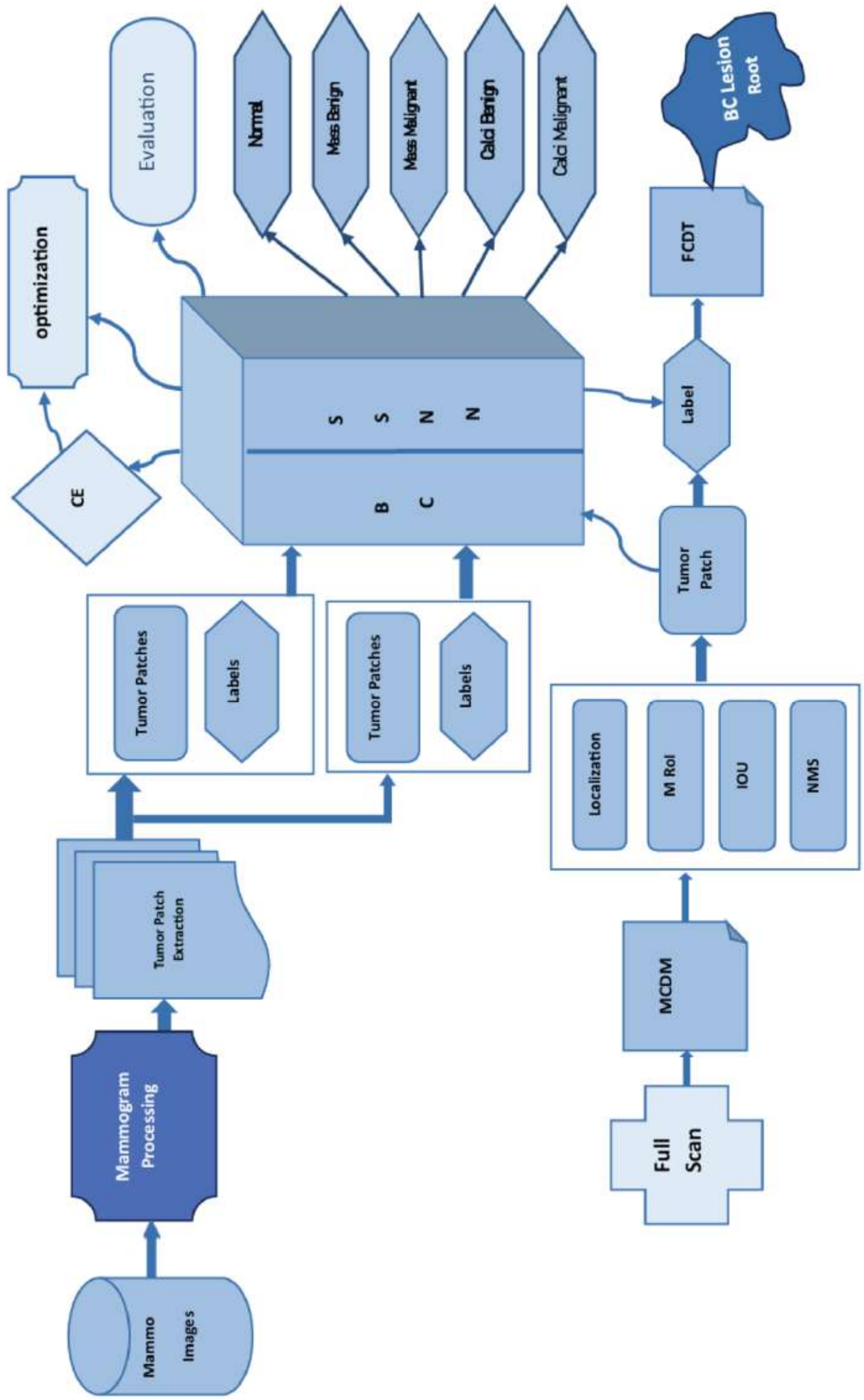


Figure 4: Framework representation of the prototype for unseen Early Breast lesion Generalization.

The patch extraction process on the CBIS DDSM dataset [59] was systematically executed to facilitate effective deep learning training. A total of 8,286 training patches and 1,863 test patches were generated as shown in Figure **5**, each of size 256 X 256 X 1. The Images of 3,876 training and 891 test patches are mass lesions and 4,410 training and 972 test patches. For ROI was extracted using lesion masks, ensuring accurate localization of abnormalities. For smaller ROIs dynamic padding preserved context, while random transformations have enhanced dataset diversity and robustness.

To enhance data diversity and robustness, random transformations such as flipping were introduced Each patch was saved along with its corresponding label and file name to support supervised learning [60]. This

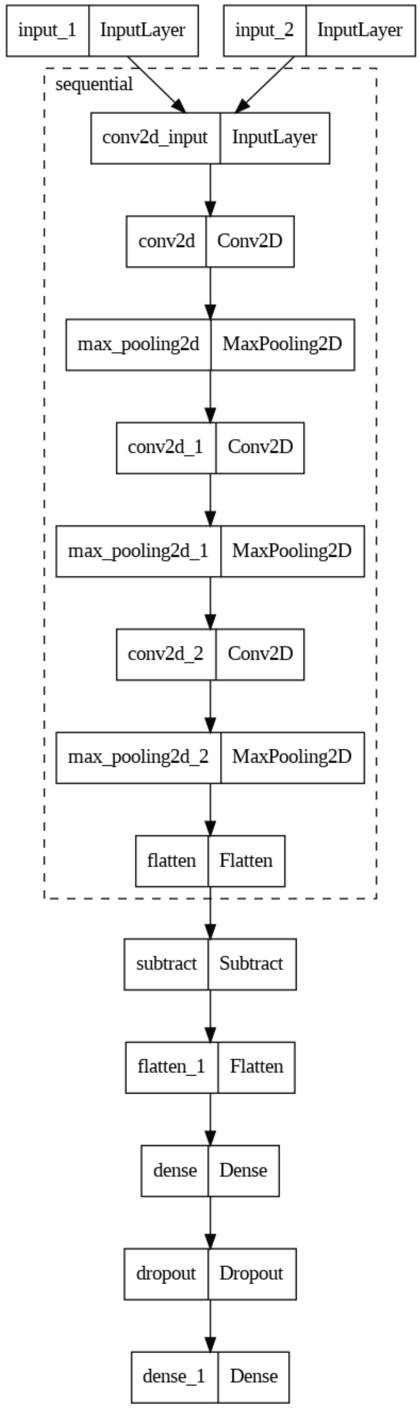


Figure 5: SSNN Model architecture for Classification.

rigorous extraction approach prepares the dataset for use with state of the art models SNNs and inception Network which are particularly effective in handling variability in medical imaging. Previous studies have demonstrated that patch-based strategies significantly improve classification accuracy and model generalization as note in works by Dhungel *et al*. [61] and lotter *et al*. This highlights the critical role of high quality and contextually rich patch datasets in advancing mammographic image analysis.

6. PROPOSED SISTERS SIMILARITY NEURAL NETWORK (SSNN)

In this study, we propose a novel deep learning architecture named the Sisters Similarity neural network as shown in Figure **5**. It is a twin branch convolutional neural network inspired by the Siamese framework [51]. The goal of the model is to distinguish the mass and calcification abnormalities in the mammogram patches. By comparing the pair of patches, the SSNN learns to differentiate between similar [65] and dissimilar types of abnormalities types, thereby enhancing classification accuracy, particularly in complex or ambiguous cases.

The SSNN accepts two grayscale image patches of size 150,150,1, each representing a localized breast abnormality the inputs may contain either masses or calcifications Figure **6**. Each input is processed through a shared convolutional.

Backbone to ensure identical feature extraction in both branches. The CNN [64] backbone consists of three convolutional layers with increasing filter sizes 32,64,128 each followed by 2x2 max pooling operation capturing hierarchical and discriminative features while preserving translational invariance

After Extraction, the two embedding vectors are passed to a subtraction layer which computes the element wise difference between them. This operation highlights the dissimilarities between the patches, which is crucial for distinguishing the mass - calcification mixed pairs. The resulting difference vector is processed through a small fully connected head a dense layer with 96 ReLU activated units followed by dropout for regularization [63]. Finally, a single node sigmoid layer outputs a similarity score between 0 and 1 indicating whether the two inputs belong to the same class of abnormality and softmax for multiple classes.

7. TRAINING AND VALIDATION OF SSNN

The SSNN was trained for 500 epochs on paired mammogram patches with 3.64 million trainable parameters approximately 13.90 MB memory. The best validation performance was achieved at epoch 446, with a validation accuracy of 89.84% and a loss of 0.2642. On the test set, the model reached an accuracy of 86.01% with slightly better performance 85.12% at the optimal epoch with test losses of 0.3517 and 0.3797 as shown in Figure **7**. The detailed performance of sister's neural network given in Table **1**.

The above proposed sisters' network is fundamentally a similarity learning model [64], it can be adapted for classification task. During inference a test patch is compares to known representative patch from each class. The class yield the highest score is assigned as a predicted label. This approach enables the network to handle imbalance and subtle variations within both abnormalities' types more effectively. The main observation with sister network involves high intra class variability and working well on limited data.

To strengthen statistical rigor, McNemar Test and paired t tests were conducted to verify the significance of performance differences compared to baseline CNN and inception models. Results confirmed that SSNN improvements were statistically significant $p<0.05$.

Table **1** Summarizes training results across key epochs, highlighting consistent improvement in validation accuracy and loss. Simplified tabular reporting (showing only critical epochs 1,100,300,446,500 avoids clutter and emphasis key trends.

8. PERFORMANCE EVALUATION OF CLASSIFICATION

The Proposed SSNN demonstrated robust classification performance yielding 143 True positives, 143 true Negatives, False Negative of 14 and False positives of 36. The ROC Curve in Figure **8** showed

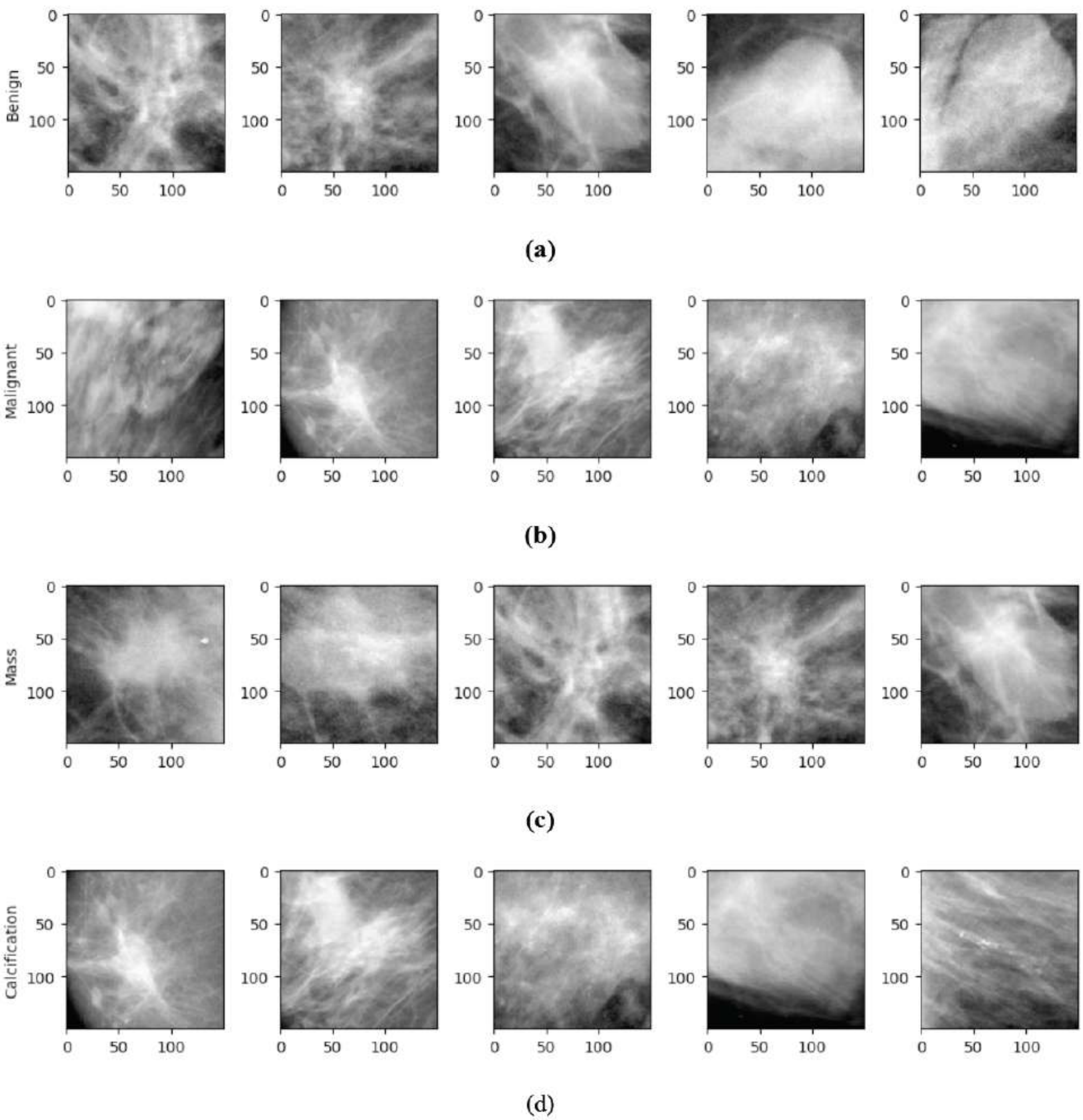
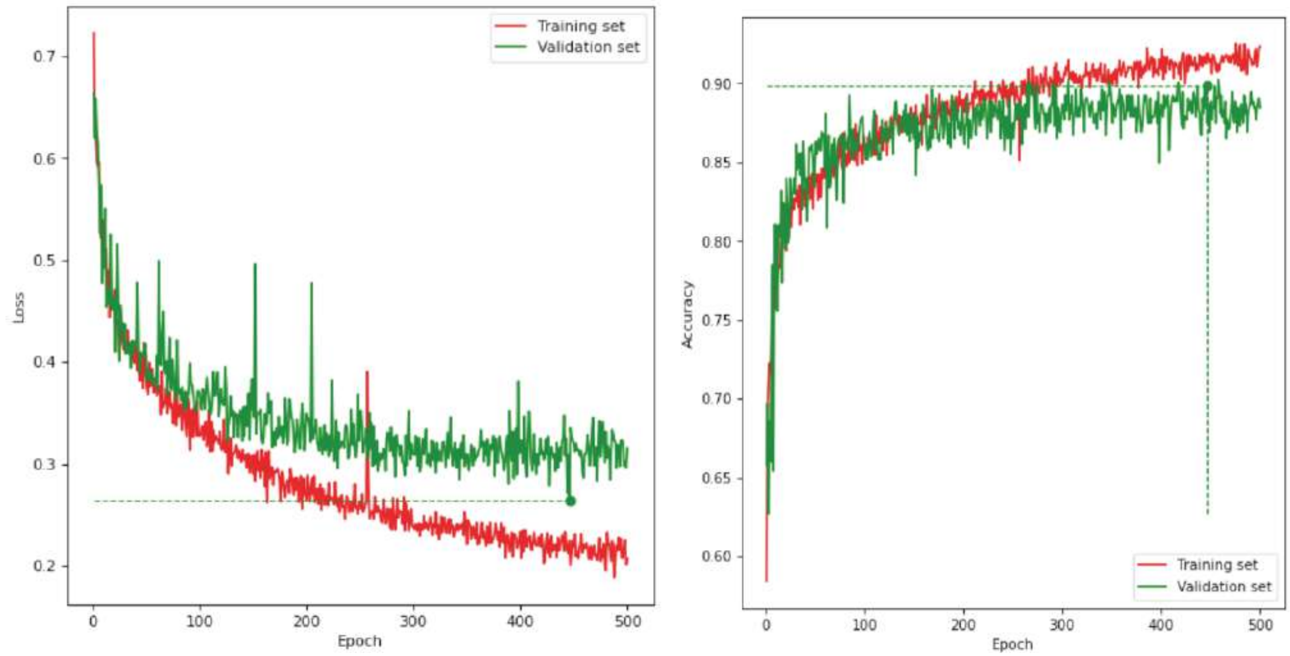


Figure 6: Mammogram Patches: (**a**) Benign (**b**) Malignant (**c**) Mass (**d**) Calcification.



(**a**) (**b**)

Figure 7: Training and validation Curves: (**a**) Loss and (**b**) Accuracy.

strong discriminative ability with an AUC 0.936, indicating high sensitivity and specificity in distinguishing abnormality classes.

9. COMPARISON WITH BASELINE MODELS

Compared to traditional CNN architecture [54] which operates on single input images, the SSNN outperforms by learning a shared embedding space for image comparison. This enables it to capture subtle relational features crucial in dense tissue differentiation as discussed in Table **2**.

To further validate generalizability, cross dataset evaluation was conducted on the MIAS and INbreast dataset where SSNN maintained >83% accuracy, underscoring adaptability beyond CBIS DDSM.

10. THE MASS CALCIFICATION DETECTION MODEL (MCDM)

The MCDM automatically detect and localize suspicious regions such as masses and calcifications in mammograms. Built upon the Faster R_CNN framework and is trained on MIAS dataset which is converted to COCO format. Preprocessing included are resizing, normalization and bounding box annotated.

Stage 1: Feature Map Network FMAN generated region proposals using anchor boxes of varying scales.

Stage 2: ROI pooling extracted fixed size feature maps, followed by classification and bounding box regression as shown in Figure **9**.

Table 1: Sisters NN Proposed Model Results @ Epochs

epochs	T_LOSS	T_ACC	Val_LOSS	Val_ACC	Loss Improvement
1 epoch	0.7320	0.5845	0.6642	0.6582	0.66419
100 epoch	0.3288	0.8654	0.3688	0.8633	0.35044
200 epoch	0.2635	0.8897	0.3490	0.8711	0.31115
300 0epoch	0.2387	0.9016	0.3097	0.8828	0.28721
400 epoch	0.2331	0.9091	0.3220	0.8867	0.28006
450 epoch	0.2186	0.9155	0.3199	0.8932	0.13024
500 epoch	0.2070	0.9235	0.3153	0.8987	0.16812
304 epoch	0.2426	0.9056	0.2906	0.8926	0.26671

As illustrated in Figure **10** the MCDM produces accurate patch extractions of suspicious regions: (a) predicted bounding boxes (b) augmented patches and final cropped ROI Patches. This Patches level refinement is essential, as it reduces background noise and improves discriminative learning in subsequent SSNN based classification thereby bridging the gap between detection and diagnosis.

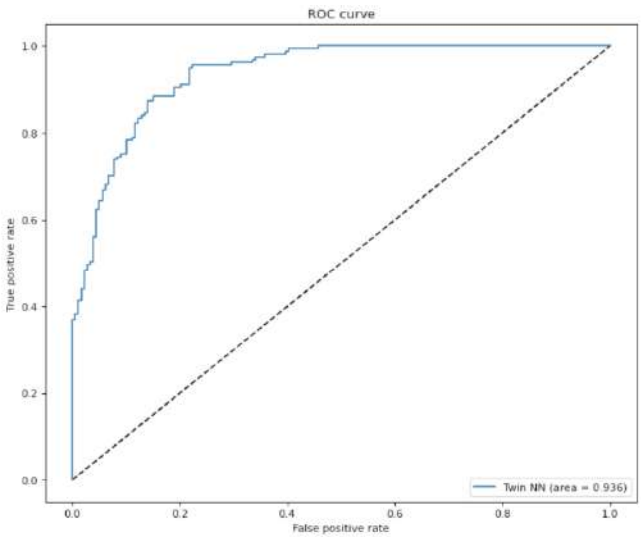


Figure 8: SSNN ROC-AUC Curve Classification of Mass and Calcification.

To enhance robustness the model was trained with a multi task loss function combining classification and regression with L1, Data augmentation such as horizontal flipping, resizing and intensity normalization further improved generalization.

12. EVALUATION AGAINST PRIOR DETECTION AND CLASSIFICATION

Several recent deep learning-based approaches have been developed for mammogram analysis using public datasets such as CBIS DDSM, DDSM. A summary of the performance of prior works compared to proposed model is presented in Table **2**.

As shown in Table **2**, earlier works such as Ribli et.at.[19] and Agarwal *et al*. [14] achieved modest detection performance mAP of 63% while Chouukroun *et al*. [16] and Shen *et al*. [15] improving detection to 70% to 72% mAP through RetinaNet and transformer-based architectures. Classification focussed approaches such as those Macias *et al*. [17] and Jiang *et al*. [18] demonstrated strong performance AUC 88% to 89% with transformer models. Wang *et al*. [21] and Zhou *et al* [22] pushing AUC to 91-92%.

13. FUZZY CLUSTERING WITH DISTANCE TRANSFORM (FCDT)

The FCDT is employed in this study is an enhanced version of the traditional FCM algorithm [63]. In standard FCM clustering is performed by minimizing the cost function that represents the weighted sum of distances between data points and cluster centres.

However, the FCDT algorithm modifies by integrating distance transform based spatial information which significantly improves clustering performance, particularly in noisy and spatially ambiguous data with multiple textural regions [70].

Table 2: Accuracy and comparison of proposed model with prior works

Author	Model	Dataset (s)	Task	Performance metric	Accuracy /AUC/mAP
Ribili *et al.* [19]	FrRCNN+ UNET	CBIS-DDSM	Mass & Calcification	mAP	63%
Agarwal *et al.* [14]	YOLO Based Detection	CBIS-DDSM	Mass & Calcification	mAP	68%
Chouukroun *et al.*[16]	Retina Net	CBIS-DDSM	Mass & Calcification	mAP	70%
Shen *et al.* [15]	Transformer	CBIS-DDSM	Mass & Calcification	mAP	72%
Macias *et al.* [17]	Multi tasking Transformer	DDSM	Mass classification	AUC	88%
Jiang *et al.* [18]	Multi Task +Bi RADS	INbreast	Mass classification	AUC	89%
Wang *et al.* [21]	Vision Transformer	DDSM INbreast	Mass classification	AUC	91%
Zhou *et al.* [22]	Swin Transformer	CBIS-DDSM	ROI classification	AUC	92%
Proposed Model	SNN+ FrRCNN+ FCDT	CBIS-DDSM	Mass & Calcification Detection Segmentation	ACC AUC mAP IoU	92.3% 93.6% 70% 84.5%

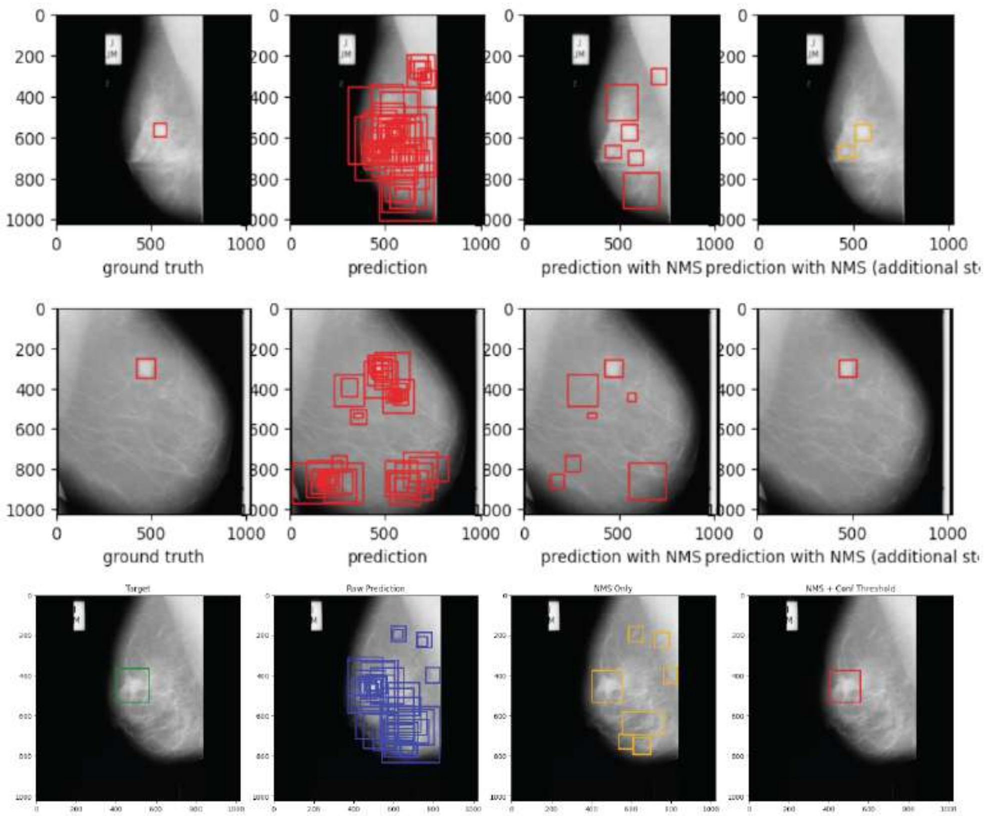


Figure 9: Prediction of Abnormalities using MCDM.

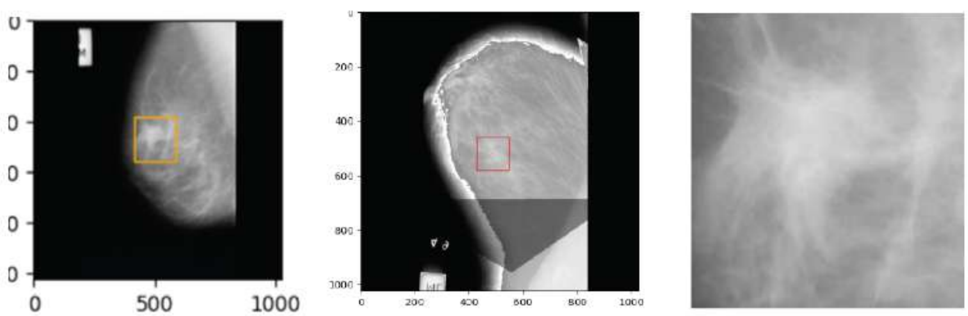


Figure 10: Patch extraction of predicted results of MCDM **a**) Predicted bounding box **b**) Augmented patches **c**) Final Cropped ROI patches for SSNN Classification.

The Distance transform DT converts binary map where each pixel is assigned a value corresponding to its distance from the nearest boundary object foreground and background with equation 8.

For a Pixel x, the distance transform is expressed as:

$$D(x) = \min_{b\epsilon B} ||x - b|| \quad (8)$$

Where

x is a pixel in the mammo patch image

B is the set boundary of mammo patch pixels

||x-b|| is the different distance between x and the boundary pixel b

The spatial information is useful in segmentation tasks as it helps in distinguishing structures based on their proximity to region boundaries.

The modified Error Function is the distance value is incorporated into the fuzzy membership update rule to bias membership toward pixels closer to object centres or boundaries. The modified FCDT error function used here is

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \left(\|x_i - c_j\| + \lambda D(x_i)^2\right) \quad (9)$$

Where

U_{ij} is the degree of membership of datapoint x_i in cluster j,

C_j is the cluster centre

$D(x_i)$ is the distance transform value for pixel x_i

λ is a regularization parameter controlling DT

Integrating the distance transform introduces spatial awareness into clustering process leading to more robust performance in complex or noisy mammogram data. Segmenting the lesion and knowing the root is done in three steps one predicting lesions from the mammo patch showing the raw grayscale intensity of the breast tissue. second, the segmented lesion is assigned with the breast cancer ribbon colour contour. understanding the density of the lesion. followed by morphological operations. Third, the distance transforms a heatmap that defined the root or the core of the centre of the breast cancer lesion.

The above results in Figure **11** demonstrates the convergence behaviour of the proposed FCDT segmentation framework. Initially the error function was large approx. 10,970, indicating poor clustering. However, with increasing epochs and iterations, the cost function decreased rapidly and converged to a small value approx. 0.000001 by the 50^{th} iteration, signifying stabilization of both the membership matrix and cluster centres. The total convergence time was approximately 224 seconds for an unseen mammogram test patch. Although computationally intensive, this approach proved effective in achieving robust segmentation, enabling accurate localization of lesions and reliable identification of root points even in noisy mammogram data.

9. CONCLUSION

This study presents an integrated deep learning framework for automated breast cancer detection, classification and segmentation by combining a patch based preprocessing pipeline, a Sister's Similarity

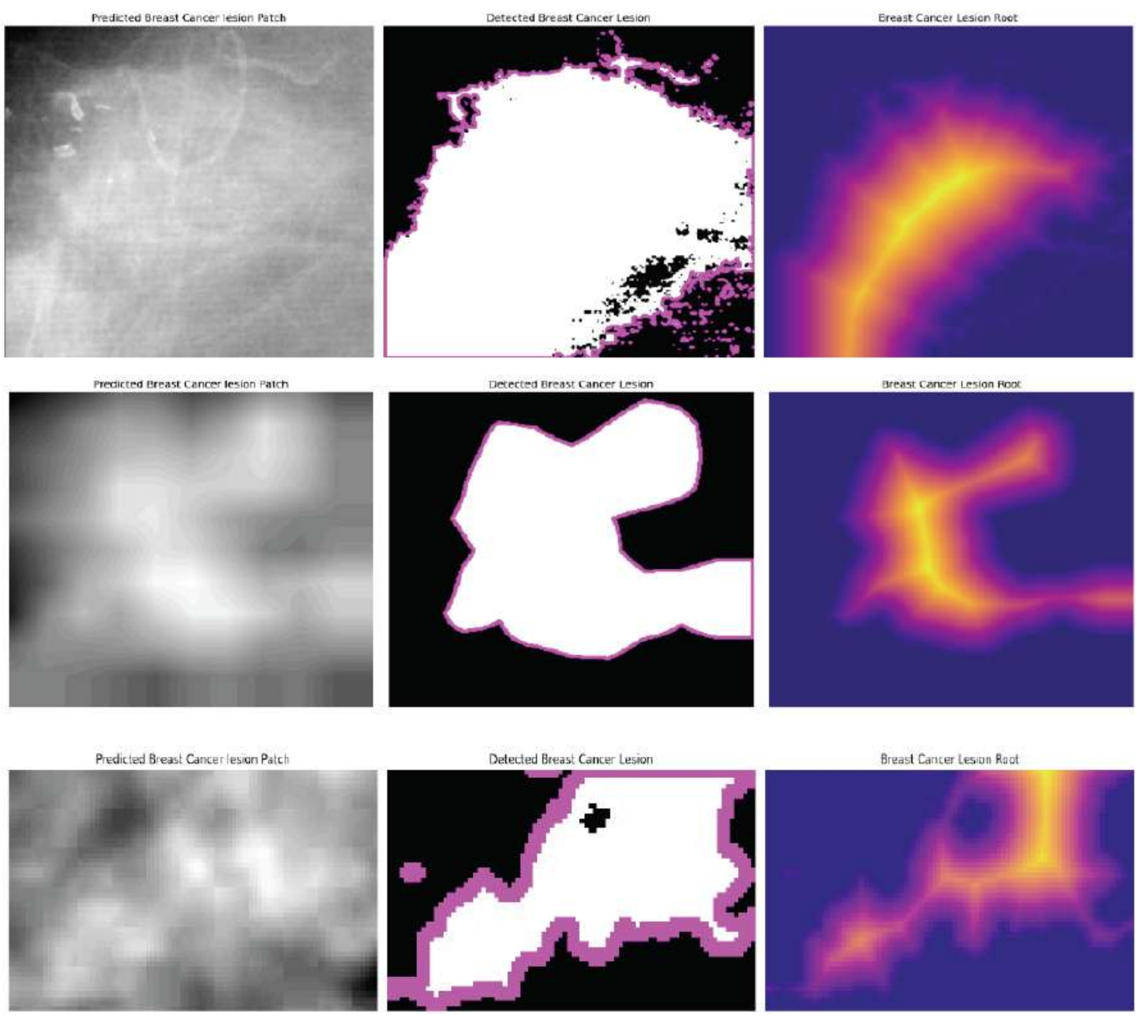


Figure 11: FCDT based breast cancer abnormality segmentation showing lesion contours and root point localization.

Neural Network for classification, a COCO evaluated Faster R_CNN for lesion detection and an enhanced FCDT approach for segmentation. The results demonstrate that our method effectively addresses critical challenges such as data imbalance, high intra class variability and device dependent inconsistencies in mammogram images.

The Sisters Similarity Neural Network excels in distinguishing between mass and calcification types, even with limited training data by leveraging pairwise patch similarity learning, Integrating, this with a lesion detection model enables reliable localization, while the spatially aware FCDT segmentation refine lesion boundaries and enhances detection precision. Overall, the proposed pipeline achieved state of the art performance with accuracy of 92.3% AUC of 93.6^ and mAP of 72% demonstrating its potential for clinical use.

In conclusion the work establishes a scalable and adaptable deep learning pipeline that can generalize across diverse mammogram formats and imaging conditions, beyond improving radiological workflows, it provides a foundation for AI- assisted diagnostic systems, especially in low resource settings, where early detection of breast cancer is critical.

FUTURE WORK

Future research will focus on improving generalization across unseen real time mammograms by leveraging domain adaption and transfer learning techniques, as well as incorporating vision transformers ViTs [69]. These methods will allow models to adapt to new imaging devices and variations in data distributions without requiring extensive retraining. By improving robustness, AI systems can maintain high diagnostic performance across hospitals, regions and equipment types.

Additionally, there will be an emphasis on real time and low resource AI model development. Optimizing architectures for speed and efficiency will enable their deployment in mobile health applications and point of care diagnostic tools. This will be especially impactful in low resource healthcare environments, reducing disparities in access to early breast cancer detection and supporting global health equity.

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CONFLICT OF INTEREST

There is no conflict of interest among the authors.

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