Journal of Integrated
SCIENCE & TECHNOLOGY

Machine-driven techniques for early-stage tumor identification and categorization in Digital Mammography: A comprehensive overview

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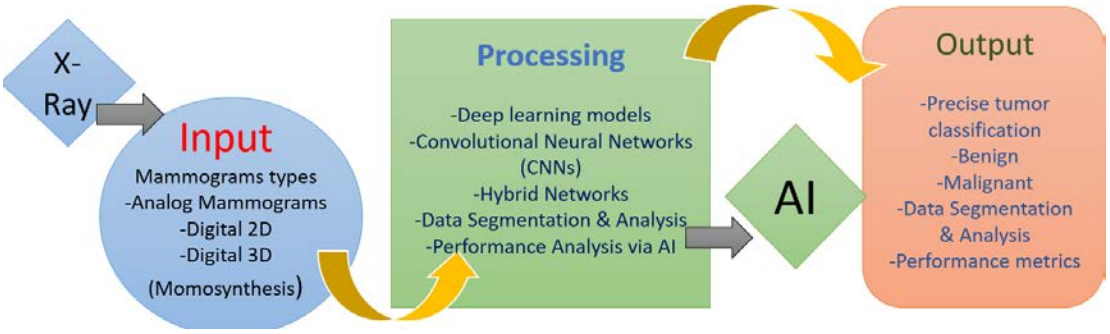
Submitted on: 27-Nov-2024, Accepted and Published on: 19-Feb-2025

Mini-Review

ABSTRACT



Breast cancer remains a critical research focus in medical image analysis, being a leading cause of mortality among women. Digital mammography enhances early detection accuracy, crucial for improved prognosis. By 2020, breast cancer is projected to account for 25% of all cancer cases, characterized by uncontrolled cell proliferation in breast tissue. X-ray imaging can reveal tumor formation, with malignancy defined by metastatic potential. Traditional diagnostic approaches, often time-consuming and operator-dependent, necessitate more efficient detection methods. This study proposes an innovative deep learning-based classification system for automated breast cancer identification using biopsy images. The model's performance is evaluated using statistical metrics including precision, recall, and accuracy. By addressing key challenges in AI-assisted risk assessment, this research aims to accelerate the integration of advanced predictive tools, potentially optimizing and personalizing mammography screening programs in the future.

Keywords: Deep learning, digital mammograms, breast cancer detection, computer-aided diagnosis, biomedical image processing

INTRODUCTION

The progressive proliferation and spread of aberrant cells in the human body are considered to be the cause of cancer. On a global scale, breast cancer has been identified as one of the leading causes of death among women.[1] The death rate from breast cancer is greater than that from TB or malaria. According to the International Agency for Research on Cancer (IARC) and the American Cancer Society, the World Health Organization (WHO) cancer research organization, there were 17.1 million cancer diagnoses worldwide in 2018 and that number is predicted to nearly double by 2026.[2] Even though medical experts and researchers have conducted considerable studies, they are unable to offer the best technique for breast cancer treatment to acquire the therapy & ensure the possibility of credible proof for its prevention.[3,4] Additionally, some crucial malignant tissue associated with cancer of the breast is aggressive & creates a greater risk to the patients since they are more prone to infect more crucial human body parts.[5,6] Women may develop tumors due to the breast cells' incredibly rapid development. The scores from the Breast Cancer Reporting & Data System (BI-RAD) determine how these huge tumor cells split into cancer cells & non-cancer cells based on the region, size & position. "Benign" describes the initial tumor region of non-cancerous tumors, whereas the term malignant refers to the supplementary

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Cite as: *J. Integr. Sci. Technol., 2025, 13(5), 1105.*
URN:NBN:sciencein.jist.2025.v13.1105
DOI:10.62110/sciencein.jist.2025.v13.1105

tumor area of cancerous tumors.[7] The lifestyles of women are not going to be at risk from benign tumors since they are curable and their growth may be controlled with the right treatments. Secondary cancers may metastasize to distant sites or neighboring tissues. Malignant tumors can spread to other bodily areas when cancer cells infiltrate the respiratory system or blood. Unchecked breast cell growth is the cause of the tumor.[8,9] Only if the patient receives the proper care, such as surgery or radiation, can a malignant tumor be cured.[3,10] Cancer cells in the Breast can damage other body organs by spreading in the nodes of lymph, such as the lungs. Invasive ductal carcinoma, the typical precursor of breast cancer, results in ductal malfunction. However, it can also start in breast tissue, lobules, and other glandular structures.[11] Additionally, the researchers discovered that adjustments to lifestyle, environment, and hormone levels all raise the risk of breast cancer.[12,13] To see the interior anatomy of the breast, low-dose X-ray imaging of the breast is used. Medical terminology for this procedure is mammography. This is thought to be the most effective strategy for finding breast cancer. Mammography exposes the breast to a significantly lower radiation dosage compared to previously employed technology.[14] It is among the most reliable screening techniques & recently been demonstrated as a major method to diagnose breast cancer.[15] Biomedical imaging is a popular study area since it may help specialized radiologists. Breast cancer investigation and treatment are greatly aided by early tumor discovery.[16] Regular screening mammography testing has been linked to lower rates of breast cancer morbidity and death, according to randomized trials and screening cohort studies.[17]

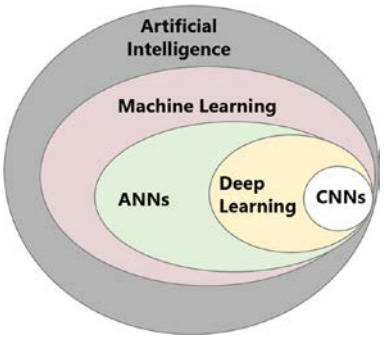

Figure 1: Diagram illustrating the connections between the various artificial intelligence approaches

Figure 1 shows a diagram illustrating the connections between the various artificial intelligence approaches. Breast cancer testing was mainly carried out using analog mammography based on screen film, Over the past two decades, the field has transitioned to entirely digital platforms. For instance, full-field digital mammography (FFDM) has enabled the transformation of pixelated data into the quasi-3D format known as digital breast tomosynthesis (DBT).[2,18] To improve the results of breast cancer screening, efforts have focused on increasing screening intervals, changing the reading formats (annual screening instead of biannual screening, double-reading instead of single-reading), and incorporating additional screening methods (mammography, ultrasound, or MRI) in addition to cancer screening.[2] While all the improved methods used for screening were able to find more tumors, the higher imaging and resource requirements generally increased false-positive rates might potentially be a function of screening intensity.[2] As a result, there has been an increase in support for "personalized" breast cancer screening programs that are related to a mix of demographics and imaging, where available, genetic data, and are customized to a specific woman's breast cancer risk.[8,19] The inclusion of image-derived data into breast cancer risk evaluation algorithms should enhance screening algorithms while maintaining harm-benefit ratio equilibrium. In this work, a systematic literature review is provided to understand the current standing of machine learning techniques for breast cancer detection from mamograph images.

DEPENDABLE AND REPEATABLE BREAST DENSITY MEASUREMENT FOR MORE ACCURATE RISK ANALYSIS

Jia Ou et al classify the greater level local auto connection characteristics of histopathology images. [20] A methodology used to automate categorization for breast malignancies in histological images was proposed by Luiz S. Oliveira et al.[21] This dataset includes 7909 images of breast cancer from 82 people. The accuracy range is between 80 and 85%. Maruf Hossain Shuvo and colleagues presented research that featured a Wavelet neural network classifier.[22] As a synthetic neural network, this Wavelet neural network operates, Mammography pictures are mainly utilized in modern medical strategies to detect breast cancer.[18]

DL techniques have recently attracted considerable interest in image identification, segmentation, detection, and computer vision.[3,21,23–25] The American College of Radiology's (ACR), Breast Imaging-Reporting and Data System (BI-RADS), Breast Density-Reporting & Data System (BI-RADS), etc provide standardized guidelines for interpreting and reporting breast imaging findings and assessing breast density, respectively. It has been well-established for some time that considerable variation exists among readers in assigning breast density, particularly for those with less experience. The accuracy rates for this assessment have been observed to range from 0.4 to 0.7. Multiple research created various DL systems with several topologies that can categorize mammographic images into BI-RADS density types with the help of evaluations provided by radiologists to improve reliability in breast density assessment.[11,24,26–29] (Table 1). In a study by Mohamed et al.[30], transfer learning with the AlexNet architecture was applied to raw FFDM images from 1427 women, resulting in an AUC of 0.94 for BIRADS density classification. The researchers noted that the model's effectiveness varied depending on the FFDM view type, with mediolateral oblique (MLO) views yielding higher accuracy (AUC = 0.95) compared to craniocaudal (CC) views (AUC = 0.88).[27] This assessment was conducted using a separate dataset comprising 963 women. Additionally, Lehman et al.[23] created a DL model utilizing the ResNet-18 architecture, which demonstrated strong concordance with 12 radiologists (four-class kappa (K) = 0.67) when applied to a substantial dataset of processed FFDM images from 39,272 women. The model underwent further evaluation on 500 randomly chosen FFDM exams, with five radiologists achieving a four-class kappa (K) of 0.78.

Table 1: Literature Review

Title of Paper	Methodology			Model Designed			Model performance
	Image format	# images(# women):	Vendors (# sites):	Model architecture:	Output density measure	Density maps	
Model development dataset Kallenberg et al.[31]	FFDM (Raw)	N/R (493 women)	Hologic (1 site)	CSAE	APD%	Yes	DSC-63% in dense tissue segmentation
Model development dataset Li et al. [10]	FFDM (Raw)	661 images (444 women)	GE (1 site)	CNN	APD%	Yes	DSC= 76% dense tissue segmentation
Model development datase. Haji Maghsoudi et al.[25]	FFDM (Raw)	15,661 images (4437 women)	Hologic (2 Sites)	U-net	APD%	Yes	DSC = 92.5% in breast segmentation APDdiff = 4.2–4.9%
Model development dataset Mohammed et al.[32]	FFDM (Processed)	15,415 images (963 women)	Hologic (1 site)	CNN AlexNet	BI-RADS density	--	AUC = 0.95 for MLO views , AUC = 0.88 for CC
Model development dataset Mohammed et al. [30]	FFDM (Processed)	22,000 images (1427 women)	Hologic (1 site)	CNN AlexNet	BI-RADS density	--	AUC = 0.94
Model development dataset Ciritsis et al. [27]	FFDM	20,578 images (5221 women)	N/R (1 site)	CNN	BI-RADS density (consensus of 2 interpreting radiologists)	--	AUC = 0.98 for MLO views AUC = 0.97 for CC views
Model development datase.	FFDM (Raw)	108,230 images (21,759 women)	GE, Kodak, Fischer (33 sites)	ResNet-50	BI-RADS density (92 interpreting radiologists)	--	Four-class K = 0.67
Chang et al. [23]		women)					
Model development dataset Perez Benito et al. [33]	FFDM (Processed)	6680 images (1785 women)	Fujifilm, Hologic, Siemens, GE, IMS (11 sites)	ECNN	BI-RADS density (2 interpreting radiologists)	Yes	DSC = 0.77
Model development dataset Deng et al. [24]	FFDM	18,157 images (women)	Hologic (1 site)	SE-Attention CNN	BI-RADS density	--	Acc = 92.17 %
Model development dataset Naik et al. [34]	FFDM	410 images (115 women)	Siemens (1 site)	cGAN, CNN	BI-RADS density (92 interpreting radiologists)	Yes	DSC = 98% in dense tissue segmentation
Model development dataset Roth et al. [23]	FFDM (Processed)	109,849 images (N/R)	N/R (7 sites)	DenseNet-121	BI-RADS density	--	Four-class K = 0.62–0.77
Model development dataset Matthews et al. [35]	FFDM (Processed) & SM	FFDM: 750,752 images (57,492 women) SM: 78,445 images (11,399 women)	Hologic (2 sites)	ResNet-34	BI-RADS density (11 interpreting radiologists)	--	Four-class K = 0.72 for FFDM, Site 1 Four-class K = 0.72 for SM, Site 1 Four-class K = 0.79 for SM, Site 2
Model development dataset Dontchos et al.[36]	FFDM (Processed)	N/R (2174 women)	Hologic (1 site)	ResNet-18	BI-RADS density (13 interpreting radiologists)	No	Dense versus non-dense Acc: 94.9% (academic radiologists) 90.7% (community radiologists)

Model development dataset Short-term risk assessment Lotter et al. [3]	FFDM (processed) DBT (MSP)	N/R (> 1000 cases; 62 K controls)	GE, Hologic (7 databases/sites)	RetinaNet	BI-RADS density (13 interpreting radiologists)	No	AUC = 0.75–0.76
Model development dataset Ha et al. [37]	FFDM (Processed)	N/R (210 cases; 527 controls)	GE (1 site)	CNN	BI-RADS density (13 interpreting radiologists)	No	OR = 4.42 Acc = 72%
Model development dataset Yala et al.[28]	FFDM (Processed)	88,994 images (1821 cases; 38,284 controls)	Hologic (1 site)	ResNet-18	BI-RADS density (13 interpreting radio logists)	No	AUC = 0.68 for image only DL AUC = 0.70 for hybrid DL + risk factors
Model development dataset Dembrower et al. [38]	FFDM (Processed)	150,502 images (1188 cases; 10,563 controls)	Hologic (N/R)	Inception-ResNet	BI-RADS density (13 interpreting radiologists)	No	OR = 1.55 ORadj = 1.56 AUC = 0.65

SPECIFIC TECHNICAL DIFFICULTIES WITH BREAST SCREENING

AI does not have a magic solution for breast cancer risk assessment, and mammographic pictures pose several technical difficulties that go beyond adjusting a model's weight. Instead of suggesting novel architectures especially suited to this domain, most attempts to date have concentrated on applying current DL models to mammographic pictures. Developing a deep learning model for full-field digital mammography (FFDM) and digital breast tomosynthesis (DBT) images is not as straightforward as simply choosing an existing model designed for natural images and training it on a large dataset. The process requires additional effort and considerations. First, compared to ordinary natural pictures, mammographic images have a significantly larger dimensionality. This is a typical, efficient method used in DL models for natural photos because the item of interest often takes up a significant portion of the image and its macro-structure, which includes attributes like form and colour, is what counts most. Nevertheless, reducing the resolution of a high-quality mammogram can significantly affect the performance of deep learning models, especially when assessing breast cancer risk. This is because subtle parenchymal patterns or tiny calcifications associated with breast cancer risk may be obscured or lost in the process. The CC view, as well as the MLO view, are the two views that make up mammogram imaging for every breast. Radiologists typically find a pattern more believable in practice if it is apparent from both angles. However, this outlook association in DL methods to risk of breast cancer evaluation has received relatively little attention. The variance in mammographic pictures produced by various technicians, suppliers, and units must also be taken into account by DL models. Normalizing mammographic images from different manufacturers is challenging, particularly because raw image data is rarely stored. This difficulty arises from the fact that each manufacturer employs its own proprietary post-processing software to prepare FFDM images for display and uses distinct methods to reconstruct individual DBT slices. The resilience of a DL model confronts substantial difficulties since vendor-specific software is often updated and picture collection parameters might vary. As a result, harmonization and quality control of mammographic pictures are important challenges that may be resolved using the AI approach.

Mammograms are used for female breast cancer diagnosis and screening. Mammograms are extremely low-intensity X-rays used to evaluate a person's breasts. Therefore, mammograms are typically used to detect breast cancer. These mammograms must be screened to discover breast cancer signs. There are three different types of mammography.

ANALOG (SCREEN-FILM) MAMMOGRAPHY

In this type, mammography films are created for breast imaging, and an exclusive X-ray machine is created for this purpose. The numerous X-ray rays are collected and turned into a mammography film with this equipment. The doctor will next examine this breast tissue picture film to find any breast cancer and other abnormalities.

DIGITAL 2D MAMMOGRAPHY

In this digital 2D kind of mammography, x-ray rays are captured using a particular digital camera, and a picture is created using a computer. The numerous X-ray beams used in this sort of mammography are photographed using a standard digital camera. Then, using a computer, this breast tissue is electronically sent to doctors for inspection.

3D DIGITAL MAMMOGRAPHY

A particular, more powerful processing system is used in tomosynthesis (digital 3D mammography) to turn digitised breast images into slices. Using these slices, this procedure enables doctors to detect breast cancer in its early stages. Computers are used to electronically communicate photographs of breast tissue to doctors for monitoring purposes.

The block diagram displays the various breast cancer detection techniques depicted in Figure 2. The Break-His database images of histopathological images are used in this dissertation study to identify breast cancer.

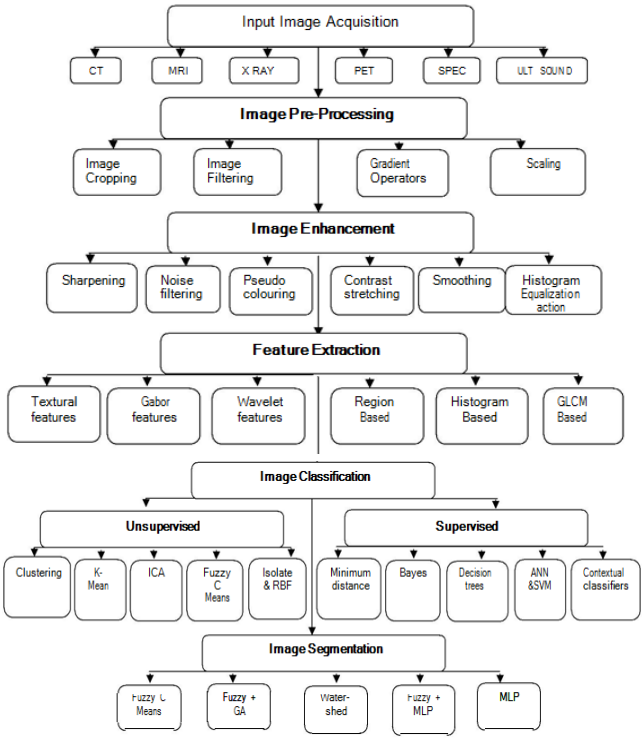

Figure 2: Different methods for processing biomedical images

Deep Convolution Neural Network Training

Deep architectures, in particular deep-feed forward neural networks, may be trained using a general framework similar to that of more traditional (less deep) models. The key methods used to train them are stochastic gradient descent and error backpropagation, specifically. However, a few particular factors must be taken into account for successfully developing deeper networks. In practice, deep networks don't perform any better than shallow ones if these issues aren't resolved. Deep learning models produce very non-linear functions because every layer in a deep network generates a nonlinearity. The input data teaches the model's parameters, such as whether the hierarchy of the model's representations is appropriate for a certain job. An optimization problem might be stated as finding a great parameter configuration for a training standard.

Suggested Deep learning models

Figure 3 illustrates a CNN architecture designed for digital mammography, specifically to classify breast tissue as malignant or benign.

Convolutional Layers extract image features like edges and patterns.

ReLU Activation Layers introduce non-linearity to model complex features.

Max Pooling Layers downsample feature maps, reducing spatial dimensions while retaining essential information.

GAP Layer (Global Average Pooling) simplifies the feature map into a single vector, reducing overfitting.

Dense Layers (fully connected) make the final classification into malignant or benign categories.

The Pause- Histopathological images are separated into two separate datasets: an examination dataset and a training dataset.

Model A

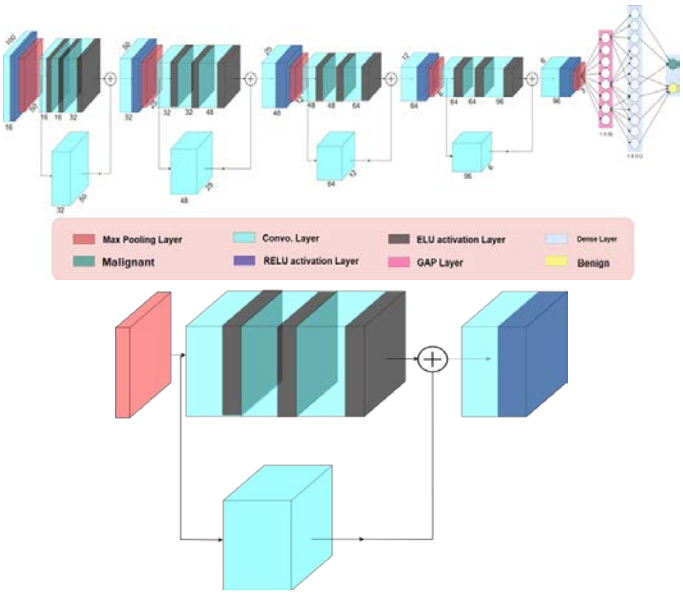

Figure 3: Residual unit of a proposed model A

Pictures used for testing are included in the test data collection. These aid in forecasting the model for this subnet. The training dataset yields the results of Histopathological images that are known to occur. The residual unit of a proposed model A is depicted in Figure 3. The suggested method makes sense of these images from the training data set for the subsequent computations. This dataset frequently displays features with a wide range of ranges, units, and magnitudes. Since most algorithms use the Euclidian distance between two locations to calculate these characteristics, it is necessary to bring all features to the same level of magnitude for this purpose.

This architecture helps in identifying breast abnormalities from mammograms effectively.

Figure 4 depicts a Convolutional Neural Network (CNN) structure designed for examining digital mammography images to differentiate between malignant and benign breast tissue. A brief overview of its elements and process is as follows:

Mammogram Input:

The starting point is a mammogram image, represented as a three-dimensional tensor (height, width, and depth).

Convolutional Layers (Blue Sections):

These layers identify crucial features in the mammogram, such as edges, patterns, and textures associated with breast tissue.

The complexity of these features increases with each subsequent layer.

ReLU Activation Layers (Gray Sections):

These apply non-linear transformations to boost feature learning and enhance the model's effectiveness.

Max Pooling Layers (Pink Sections):

These layers reduce the spatial dimensions, decreasing image size while preserving key features, thus improving computational efficiency.

Global Average Pooling (GAP) Layer (Pink Rectangle):

This layer condenses the feature maps into a compact representation, minimizing overfitting & enhancing generalization.

MODEL B

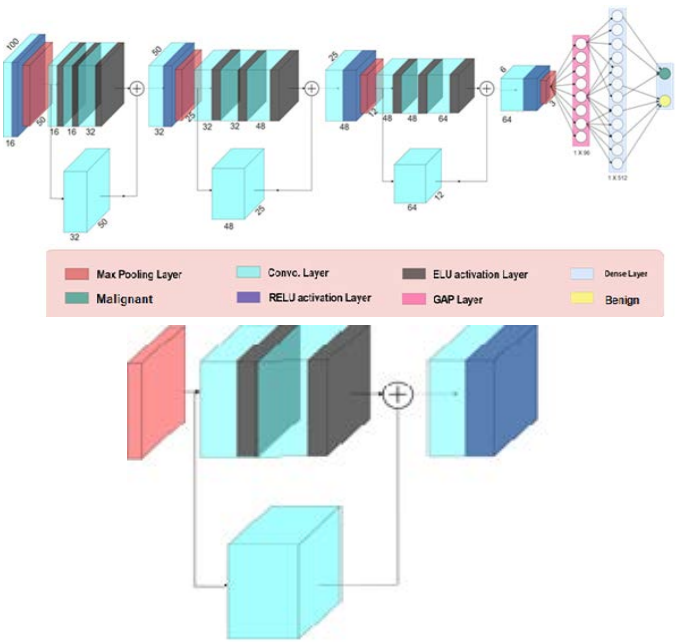

Figure 4: Residual unit of a proposed model B

Dense Layers (Pink and Yellow Circles):

These fully connected layers process the features and perform the final classification.

The final layer categorizes the image as either

malignant (blue)

or

benign (yellow).

This CNN architecture is specifically designed to identify abnormalities in mammograms, assisting in breast cancer diagnosis by distinguishing cancerous tumors from non-cancerous tissues.

To do this, scaling is used. Scaling involves transforming and fitting the provided data into a certain scale. The algorithm selection is used by the machine to learn any dataset to provide superior outcomes. Therefore, the two classification groups that are presented for the selection purpose of the database are unsupervised learning and supervised learning. Unsupervised learning involves extracting data directly from a dataset without any supervision. The information that was not labelled nor classed was utilised by this method. Residual unit of a proposed model B is shown in Figure 4. The knowledge acquired for supervised learning is necessary for both the desired output and input. The fundamentals of learning are presented for the categorization of the input and output data for future data processing. In a supervised learning method, the classification problem and the regression problem are the two classification issues that are presented. While weight and salary are examples of regression issues, the categorization of emails as spam or not is an example of a classification problem. A schematic of the Hybrid Deep Convolutional Networks For Breast Malignant Detection for histopathology images is shown in Figure 5.

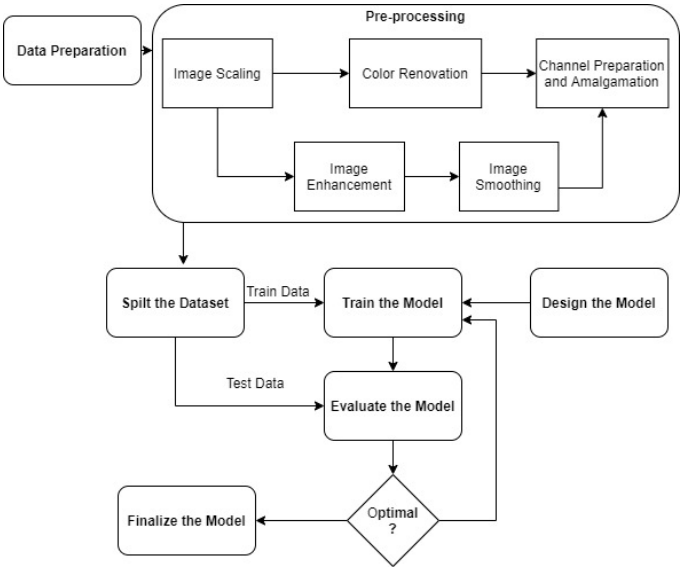

Figure 5: Overview of the suggested approach

LIMITATIONS OF CURRENT METHODOLOGIES AND THE PROPOSED ENHANCEMENTS IN THE SUGGESTED APPROACH

The limitations of traditional techniques are highlighted, including lower accuracy rates and ineffective differentiation between benign and malignant tumors. A research gap is identified, emphasizing the necessity for improved algorithms to enhance tumor detection and classification precision, particularly in complex cases where atypical tumor characteristics are exhibited. To address these gaps, an approach integrating advanced machine learning techniques and image processing methods is proposed. This integration is anticipated to improve diagnostic accuracy and reduce false positives and negatives in mammography readings. The importance of developing a more robust framework is emphasized, with the aim of adapting to various imaging conditions and patient demographics. Ultimately, this approach is expected to lead to improved patient outcomes in breast cancer detection and diagnosis.

CONCLUSION

The malignancy of breast tumours is thoroughly analysed in this study for the thesis. In this thesis work, a comparison of many contemporary techniques is also included. It is obvious from this comparison that the planned study efforts produce better performance results than alternative approaches. Break-Up Histopathological Images His dataset, which was used in this article, demonstrates precise breast tumor malignancy identification. The many channels in the images are given prominence in the intended study efforts for any deep learning model. AI's growth and use in breast cancer detection are expected to enhance risk evaluation for the disease and enable individualized screening suggestions.

Unfortunately, there are still a lot of technical issues with mammographic scanning that need to be resolved, particularly when mammographic computed tomography and AI technologies merge. Additionally, it is crucial to improve the repeatability, explainability, and durability of AI breast cancer risk models

utilizing large, diverse datasets to hasten their validation and transfer into clinical deployment. AI will revolutionize breast cancer screening by using inventive ways to increase accuracy, validate performance, and foster trust in decision-making.

AUTHOR CONTRIBUTION

Conceptualization: Ravindra Moje (R.M.), Harshada Mhetre (H.M.); Writing—Original Draft Preparation, Ravindra Moje (R.M.), Harshada Mhetre (H.M.); Writing—Review and Editing: Mangal Patil (M.P) Prashant Chougule (P.C), Pramod Jadhav (P.J.),Priyanka Paygude (P.P), Shwetambari Chiwhane (S.C). All authors have read and agreed to the final version of the manuscript.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

FUNDING STATEMENT

This research received no specific grants from any funding agency in the public, commercial, or not-for-profit sectors.

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