How to Cite:
Punitha, M. (2022). Hybrid DLDT algorithm based tumor classification of mammogram images. *International Journal of Health Sciences*, *6*(S10), 1032–1041.
https://doi.org/10.53730/ijhs.v6nS10.13772

Hybrid DLDT algorithm based tumor classification of mammogram images

M. Punitha
Head & Assistant Professor, Mangayarkarasi College of Arts and Science for Women, paravai, Madurai, TamilNadu, India
Corresponding author email: punitham2883@gmail.com

***Abstract*---**Despite the fact that current classical image classification techniques have been widely used to address real-world problems, these applications are frequently hampered by problems including disappointing results, poor classification accuracy, and constrained adaptability. This method separates the mammography image tumour feature extraction and classification processes. The effective way to improve the accuracy of mammography image tumour classification is to integrate the feature extraction and classification processes using the potent deep learning model. The deep structural advantages of multilayer nonlinear mapping and the tumour representation of well-multidimensional data linear decomposition, however, are fully utilised in this paper, which also introduces the idea of tumour representation based on shape-based feature extraction into the architecture of the deep learning network.

***Keywords*---**deep learning, shape-based feature extraction, decision tree.

Introduction

One of the most prevalent types of cancer among women worldwide is breast cancer. Breast cancer's survival rate is improved when it is discovered early. Therefore, routine examinations are seen to be one of the most crucial techniques for aiding in the early diagnosis of this type of cancer. One of the best screening techniques for early breast cancer diagnosis is mammography, which can identify a number of abnormalities in the breast before symptoms arise. A number of studies on breast cancer detection and classification have been put forth in an effort to develop more potent classification methods for breast cancer detection in light of the substantial advancements in deep learning and image processing techniques. The deep learning idea aids in the more accurate tumour detection in breast imaging. The approach is a deep-leaning concept, making tumours in mammography images more easily reproducible.

Manuscript submitted: 9 August 2022, Manuscript revised: 18 Oct 2022, Accepted for publication: 27 Nov 2022

Related Works

Jun-e-Liu et al. [1] proposed the Image classification algorithms based on the stacked sparse coding depth Learning model Optimized Kernal functions to non-negative sparse representation as well as the Traditional Image Classification methods Medical Problems and separate image features extraction by using Deep Learning model with accuracy. In summary, it has a superior ability to resolve issues and perform Complex Function. NeerajDhungel et al[2] .'s exploration of the applications of deep convolutional and deep belief networks focuses primarily on the estimation of structured prediction models using loss minimization parameters learning algorithms and the use of conditional random fields and structured support vector machines. Finally, Indrajat Kumar et al. [3] draw the conclusion that Reset 18 model &Rehu activation function yield should have received the Outstanding performance for this Research. They introduced the numerous classification approaches and companions best accuracy dense detection. Nada M. Hussan et al. [4] introduced the survey on Breast cancer CAD system for mass detection and classification technique for the novelty survey. They gave many of the preprocessing, segmentation, feature extraction, and classification technique moves in CAD systems and compared the timeline for the development of Breast Cancer CAD systems. The main goal of this paper is to identify the disease in the field of medical image processing. Suganys Devi et al.[5] reviewed the Medical Image analysis with Deep Learning techniques and Artificial Intelligence. This Deep Learning Networks can be evaluated and applied to the Big Data in the field of medical image processing. The main goal of this paper is to identify the disease in the field of medical image processing. Suganya Devi et al.[6] reviewed the Medical Image analysis with Deep Learning techniques and Artificial Intelligence. This Deep Learning Networks can be evaluated and applied to the Big Data in the field of medical image processing.

Mehedimased et al.'s[7] seven pre-trained models for convolutional neural networks were presented, and they achieved 92% accuracy and a 0.972 Acc score. Gradually generated heat maps further demonstrate how well the pre-proposed model pulls key characteristics for breast cancer classification. In this study, Xiaogin Wang et al.[8] introduced Deep Learning in Medical Image Processing, which has the fastest method for diagnosing diseases, classifying images, and making deep learning models appear appealing before usage, particularly for the diagnosis of women's breast cancer. Boot Thomas et al. [9] proposed a method for detecting breast cancer using deep learning in the novel stage. They used convolution neural networks, placed them at the top of the margin, and concentrated on the breast image's shape to find the tumours. They used 1200 images and discovered a tumour detection rate of 0.892 micro average percentage. In order to help discover the cancer in breast images, Vaira Suganthi Gnanojendran et al. [10] introduced the emphasis on computer-aided systems of breast cancer detection by applying deep learning techniques. They employed many classification techniques as well as machine learning algorithms. Yuliana Timenez-Gaona and colleagues[11] Analyzes breast image detection for breast cancer critically using a variety of complex categorization, preprocessing, convolutional neural networks, and evolutionary matrices. Fernando Tavier To discover the malignancies in a breast picture, Reves Benito et al.[12] offered the novel ways of completely convolution Neural Networks to introduce a Deep learning with SAUF / Scan Plus array based union find algorithm. In their study on breast cancer in bones using deep learning and convolutional neural networks, Nikolaospapandrianos et al.[13] also utilised the potent automatic classification CNN architecture for medical imaging algorithms Resnet 50, VGG16, Mobile Net, and Dense Net. By focusing primarily on a four class K of 0.667 and categorising the dense model models, Ken Chang et al. [14] established a novel strategy for detecting breast cancer. Deep learning-based artificial intelligence systems were proposed by Mona Altiti et al.[15] as effective ways to diagnose breast cancer. major shift and scale issues are resolved, and the technique is based on inverted rotation. Finally, they assess the outcome using image quality metrics. Retina net categorization and the (YOLO) You Only Look Once were introduced by GhedaHamed et al. [16] and used in a comparative investigation.

Methodology

In this study, we presented three cutting-edge phase-specific innovative techniques. Each stage is distinct and serves a particular purpose. Here, one of the better pre-processing methods was employed. Deep learning-based decision tree ideas are used for segmentation, feature extraction, shape-based tumour prediction, and classification.

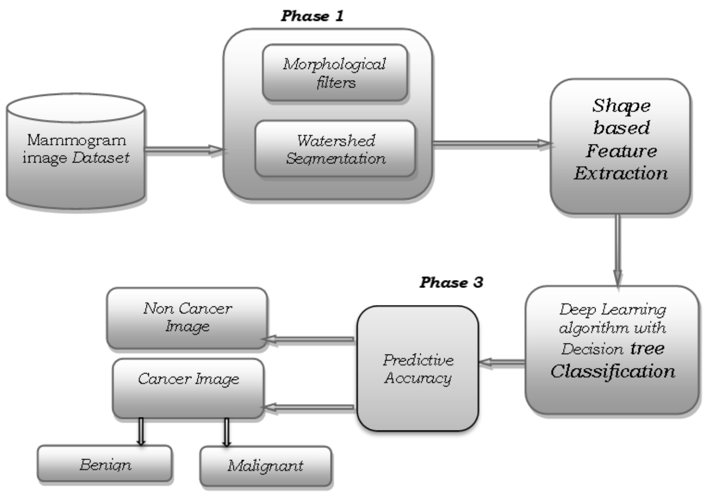

Figure 1. Process flow Diagram

Phase 1: Preprocessing and segmentation has been done this phase
Phase 2: Feature Extraction has been done by shape based feature extraction technique
Phase 3: Classification has been done through Deep Learning with decision tree classification.

Pre-Processing

The morphological filter concept is dwindling and allowing growth to proceed. The term "shrink" refers to the process of removing tiny and large structures using a median filter, and then expanding back the remaining structures by the same amount. In this instance, we choose the open and close operation. While the close operation eliminates pixels from the given input images and acts as an independent process in the supplied input mammogram images, the open operation can add pixels in the input mammogram images.

Watershed Segmentation

The watershed algorithm is built on collecting specific background and foreground, then using markers to let watershed run and discover the exact boundaries. Typically, this approach makes it possible to find touching and overlapping objects in images. Using the distance transform, locating the certain foreground Unknown area is the region that is utilised as a marker for the watershed algorithm and is present in both the foreground and background. The increased use of data visualisation is disrupting imaging procedures. Deep learning technology has entered the space with a cutting-edge method for analysing multidimensional images.

Shape based Feature Extraction

Finding the imperfect or tumour instances of an object in the provided mammography image is the major goal of the proposed work. Here, features from the segmented mammography picture are retrieved, with a particular emphasis on shape-based features. similar to the mammogram's CALC function. The final feature extraction image is crucial for determining whether or not the mammography image should show a malignancy. Shapes play a crucial influence in society. It has no discomfort or feel, thus it's at a benign stage. Another feature is having the unic techniques in CALC features like small dots of calcium divided in the breast. The decision has been made based on the features, and deep learning with decision tree is employed to quickly compute the tumour feature.

Deep Learning algorithm with Decision tree Classification

Deep learning models have been created in the last 20 years, dramatically increasing the types and numbers of problems that can be solved by neural networks. Deep learning isn't just one method; rather, it's a collection of calculations and spatial patterns that may be applied to a range of issues. Despite being more than 70 years old, connectionist structures are now at the forefront of artificial intelligence because to modern architectures and GPUs (graphical processing units). For the prediction of tumour detection in a picture, a shape-based classification framework for deep learning is provided. In the development of tumour identification in mammography pictures and other study fields, deep learning (DL) model plays a vital role in the most current trends in artificial intelligence. Deep Learning is a subset of machine learning that uses a neural network to learn underlying features from data. Although it is commonly known that the performance of machine learning-based frameworks suffers when dealing with massive amounts of data, deep learning models exhibit promising results. In contrast to the Deep Learning model, which derives high-level features directly from the data, a key drawback of the Machine Learning method is that it learns from manually built features, which are laborious, fragile, and non-scalable.

The Deep Leaning model, which aids in the determination of malignancy in mammography pictures, is comparable to a neural network with several hidden layers, convolution layers, pooling layers, fully connected layers, activation functions, etc. The suggested method categorises the input photos' features and repeats both tumour and non-tumor images. If the image contains a tumour, classify the features according to the type of tumour image until all the requirements are met and the mammogram's feature extraction is accurate. In total, 1525 photos are used in this work, of which 900 serve as training sets and the remaining 625 serve as testing sets. The next step is to forecast which photos will be impacted by a tumour. If a tumour is visible on an imaging, determine whether it is benign or malignant. Then, a diagnosis is made using the feature classifications prediction formula on the feature extracted image. Under 35% of the prediction is regarded as a non-tumor image, between 35% and 60% as a benign tumour image, and between 60% and 100% as a malignant image. This formula generates forecasts.

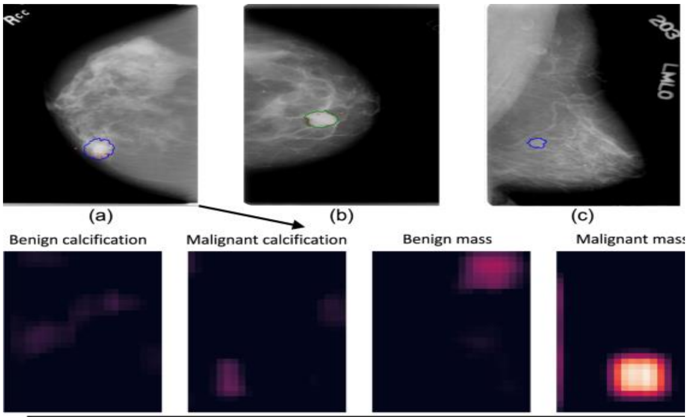

Figure 2. Deep Learning to Improved tumor detection on Digital Mammogram images

Prediction value is equal to Original value minus Prediction Value. A positive or negative value is used to diagnose a prediction, and a probability is given for both predicted malignant and benign images. The benign and malignant formula is represented in this figure.

Then, if the sigmoid function is g = 1/ (1 + exp (z)); Prob = sigmoid ([1 t m] theta g- Grad, prob- Probability, t- Clumps' Thickness, and m- Marginal Adhesion.

If the likelihood of the tumour being malignant (cancerous) exceeds 60%, the tumour is benign if the likelihood is between 60% and 35%. (non-cancerous).

Experimental validation

All of the images are prepared beforehand, and watershed segmentation techniques are used to detect the tumour utilizing segmentation and feature extraction with the use of shape-based feature extraction approaches. This lowers the noise level for each mammography image. All digital mammography images are of the highest quality, and classification problems have been solved using deep learning and decision tree prediction values. There has been no other research done, and the suggested method yields better results.According to the accompanying equations and the presence of the goal irregularity of an image, they are processable.

True Negative (TN) results in negative values for the test.
False Positive (FP): When the test results are abnormally positive.
False Negative (FN): when a clinical anomaly is present, the test result is unfavourable.

Calculate the false positive and false negative values (FP and FN, respectively). The sensitivity, specificity, and accuracy of this experiment's results can be assessed by computing them and comparing them to some other available techniques. To figure out how many tumour pixels there are Table 1 below should include tumour extracted pixels and segmented part.

Table 1
Calculate Number of pixels segmented and extracted

Image	*Total Number of Pixels*	*Tumor Extraction Pixel*	*Tumor Area (mm)*
I(1)	30154	5845	1.908
I(2)	41547	8974	2.025
I(3)	24512	4248	1.658
I(4)	35474	5478	1.701
I(5)	45237	8624	2.047

Table 1 Shows the Segmented pixel values as well as the number of pixels extracted from the given digital mammography images. Each image had the different pixel range and different tumor range. The number of pixels extracted is less than the segmented portion pixel range.

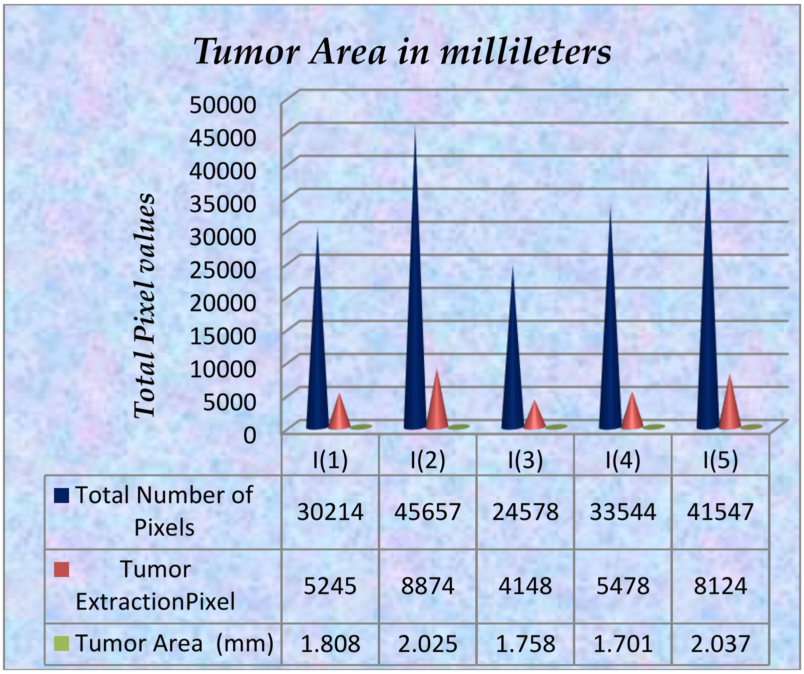

Figure 3. Evaluation chart for segmented and extracted pixel range

The segmented picture samples are represented graphically in the above figure. And the precise pixel range is shown quite clearly. Red indicates an extracted pixel range, and blue indicates a segmented pixel range. The blue colour cone depicts the segmented pixel range and the brown colour cone indicates the extracted pixel range in the graphical representation of segmented and extracted pixel ranges. Since the extracted pixel range is smaller than the segmented range, the outcome is excellent. According to the algorithm for tumour classification prediction range, the classification done should benefit from this value.

Comparison of Various Feature Extraction and classification methods

Table 5.2 compares several feature extraction and classification strategies, and the suggested methods should produce better results than the other two methods, according to this table.

Table 2
Comparison of various classification techniques

Images	Classifiers	Specificity	Sensitivity	Accuracy
I(1)	DLDT Classifiers	89%	91%	97%
I(2)		77%	67%	93%
I(3)		72%	67%	94%
I(4)		78%	73%	99%
I(5)		89%	93%	97%
I(1)	Rough Classifier	79%	80%	82%
I(2)		69%	72%	81%

I(3)		70%	72%	78%
I(4)		82%	83%	90%
I(5)		78%	59%	60%
I(1)	Fuzzy Classifier	89%	89%	90%
I(2)		79%	88%	91%
I(3)		61%	72%	80%
I(4)		82%	83%	75%
I(5)		80%	86%	89%

Original image	Feature Extracted image	Proposed DLDT Classifiers

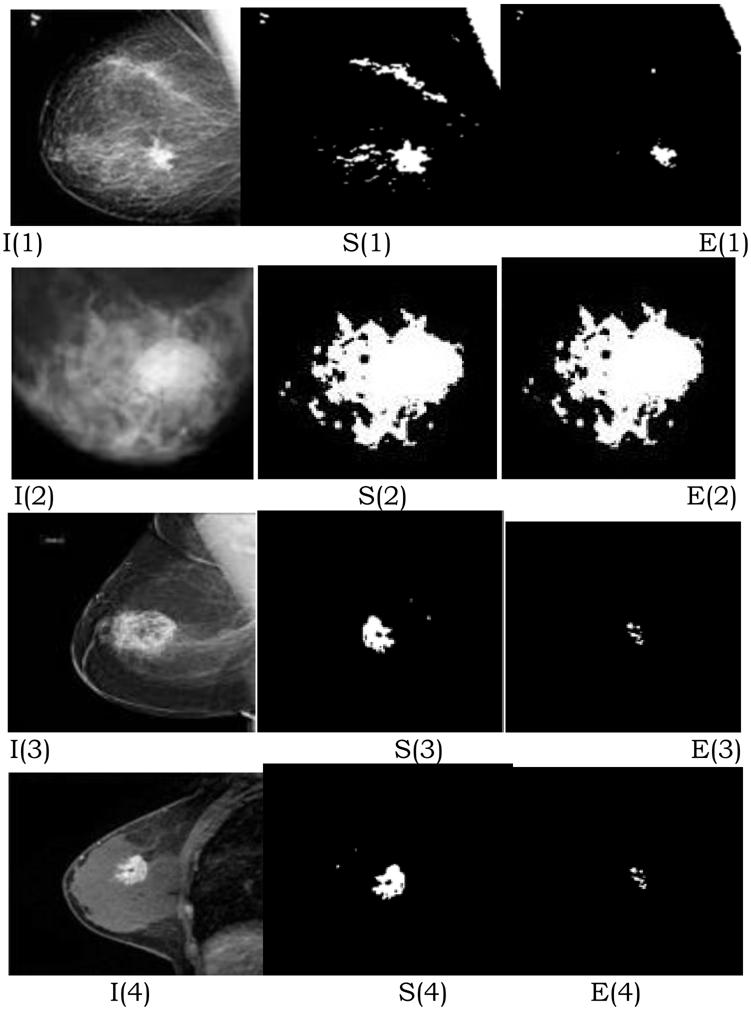

Figure 4. mammogram Feature extraction and Classification result

Figure 4: Mammogram picture input ranges from I(1) to I(5) in the first column; this range should include a tumour. The results of Feature Extraction are displayed in the second column as S (1) through S (5). The mammography pictures for tumour classification range from E (1) to E (5) in the third column. Each image had a varied pixel resolution and pixel range, and from image E (1) to image E (5), tumour pixels were classified from the retrieved image. In contrast to earlier research, the proposed method only needs a minimal number of extracted pixel values and takes less time to compute. By using these strategies, the overall time required for each photograph is also too short.

Conclusion

The primary objective of this suggested strategy was to quickly locate the tumour from the mammography image without pixel loss. Deep learning and the decision tree classification algorithm are used in this hybrid to speed up computation. Positive pixel value (PPV) and negative pixel value (NPV) prediction probabilities are used to classify tumours (negative pixel value). Clump Thickness and Marginal Adhesion, two aspects of the mammography image, are used to determine the likelihood that a tumour is malignant or benign. With the right values inserted into the formula, we can determine whether a tumour is likely to be malignant or benign. The tumour is malignant (cancerous) if the probability is greater than 50%, and benign (non-cancerous) if the probability is lower than 50%. As a result, the result, which obtained 99.02% accuracy with 5.28 minutes of computation time, demonstrates the shortcomings of high-performance computing technology. This combination of the proposed work is very beneficial for the analysis and diagnosis of medical images.

References

Boot, Thomas , Irshad, Humayun,(2022) Diagnostic Assessment of Deep Learning Algorithms for Detection and Segmentation of Lesion in Mammographic images

Francisco Javier P´erez-Benito , Fran¸cois Signola , Juan-Carlos Perez-Cortesa , Alejandro Fuster-Baggettoa , Marina Poll´anb, Beatriz P´erez-G´omezb, Dolores Salas-Trejod, Mar´ıa Casalsd, Inmaculada Mart´ınezd, Rafael LLobet (2020) A deep learning system to obtain the optimal parameters for a threshold-based breast and dense tissue segmentation

Ghada Hamed , Mohammed Abd El-Rahman Marey, Safaa El-Sayed Amin, and Mohamed Fahmy Tolba(2020) Deep Learning in Breast Cancer Detection and Classification

Indrajeet Kumar, Abhishek Kumar, V D Ambeth Kumar, Ramani Kannan, Vrince Vimal, Kamred Udham Singh, Mufti Mahmud,(2021) Dense Tissue Pattern Characterization Using Deep Neural Network

Jun-e Liu and Feng-Ping An,(2020) Image Classification Algorithm Based on Deep Learning-Kernel Function

Ken Chang, Andrew L. Beers, Laura Brink, Jay B. Patel, Praveer Singh, Nishanth T. Arun, Katharina V. Hoebel, Nathan Gaw, , Meesam Shah , Etta D. Pisano, Mike Tilkin, Laura P. Coombs, Keith J. Dreyer, Bibb Allen, Sheela Agarwal, Jayashree Kalpathy-Cramer(2020) Multi-Institutional Assessment and Crowdsourcing Evaluation of Deep Learning for Automated Classification of Breast Density

Mehedi Masud, Amr E. Eldin Rashed, M. Shamim Hossain,(2020) Convolutional neural network-based models for diagnosis of breast cancer

Mona Alfifi1 , Mohamad Shady Alrahhal , Samir Bataineh , Mohammad Mezher(2020) Enhanced Artificial Intelligence System for Diagnosing and Predicting Breast Cancer Using Deep Learning

Nada M. Hassan1 & Safwat Hamad2 & Khaled Mahar(2022) Mammogram breast cancer CAD systems for mass detection and classification: a review

Neeraj Dhungel, Gustavo Carneiro, and Andrew P. Bradley,(2015) Deep Learning and Structured Prediction for the Segmentation of Mass in Mammograms

Nikolaos Papandrianos , Elpiniki Papageorgiou , Athanasios Anagnostis, and Anna Feleki (2020) A Deep-Learning Approach for Diagnosis of Metastatic Breast Cancer in Bones from Whole-Body Scan

S. Suganyadevi, V. Seethalakshmi, K. Balasamy (2021) A review on deep learning in medical image analysis

Vaira Suganthi Gnanasekaran , Sutha Joypaul , Parvathy Meenakshi Sundaram , Durga Devi Chairman(2020) Deep learning algorithm for breast masses classification in mammograms

Xiaoqin Wang1, Gongbo Liang , Yu Zhang , Hunter Blanton , Zachary Bessinger , Nathan Jacobs,(2020) Inconsistent Performance of Deep Learning Models on Mammogram Classification

Yuliana Jiménez-Gaona , María José Rodríguez-Álvarez and Vasudevan Lakshminarayanan(2020) Deep-Learning-Based Computer-Aided Systems for Breast Cancer Imaging: A Critical Review