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Histopathology based Benign/Malignant Breast Cancer Detection using Lightweight-Deep-Learning with Fused/Ensemble Features

K. Vijayakumar[1,2], F.Sangeetha Francelin Vinnarasi[1], B. Senthilnayaki[1], Mohammad Nazmul Hasan Maziz[3], Mathiyazhagan Narayanan[4], S D Sundarsingh Jebaseelan[5]

[1]Department of Information Technology, St. Joseph's Institute of Technology, Chennai, India.

Email ID: vijay@stjosephstechnology.ac.in

[2]Postdoctoral Fellow, Faculty of Medicine and Health sciences, Perdana University, Malaysia

Email ID: k.vijayakumar@perdanauniversity.edu.my

[3]Professor, Faculty of Medicine and Health sciences, Perdana University, Kuala Lumpur

Email ID: mohammad.nazmul@perdanauniversity.edu.my

[4]Department of CSE, Saveetha Institute of Medical And Technical Sciences (SIMATS), Chennai, India.

Email ID: mathimicro@gmail.com

[5]Department of EEE, Sathyabama Institute of Science and Technology, Chennai, India.

Email ID: sundarsingh.eee@sathyabama.ac.in

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ABSTRACT

Breast cancer (BC) is emerged as one of the harsh cancer in women which causes a large diagnostic burden globally. Early diagnosis and treatment is very essential to save the patient from the BC. Clinical level detection of the BC is commonly performed using the image supported methods which includes; (i) initial screening with a chosen traditional imaging technique, and (ii) histopathology-image (HI) supported cancer and its severity confirmation. The HI-based examination is essential to know the severity of the BC, which further supports the type of the treatment, needs to be planned and executed. The proposed study aims to develop a lightweight-deep-learning (LDL) tool to detect the benign/malignant BC using the chosen HI-data. The stages in this scheme includes; data collection and image size modification to 224x224 pixels, feature extraction with a chosen LDL-model, classification with SoftMax to identify the best model, and executing the classification with fused/ensemble deep-features to achieve better BC detection based on the chosen classifiers. This work implemented 3-fold cross validation and the outcome of this study confirms that the implemented LDL-model provided a detection accuracy of >98% with Random Forest classifier when ensemble feature is considered

Keywords: *Healthcare; Breast cancer; Histopathology; Deep learning; Detection.*

1. INTRODUCTION

In recent years, Breast Cancer (BC) has emerged as one of the most prevalent and challenging forms of cancer that affects women all over the world. It is also a substantial contributor to the global health pressures, that includes diagnostic and treatment burdens. Based on the statement of recent research works, the BC is declared as the significant cause of the cancer occurrence and deaths among females. This situation highlights the significant need for premature detection and precise intervention to improve survival rates for individuals affected by the BC. The intricacy of BC, in conjunction with the heterogeneous character of the disease, makes it necessary to have improved diagnostic procedures that are able to accurately differentiate between benign/malignant cases. It is essential to differentiate in this way in order to develop treatment regimens that are effective [1,2].

Historically, physicians used a combination of clinical examinations, imaging modalities, and histological assessments to diagnose BC. Biopsy based sample collection and histopathology based examination continues to be the gold standard among these methods for determining the presence and harshness of the BC. The histopathological-image (HI) based examination of BC involves a microscopic study of tissue samples collected using biopsy to recognize the malignancy in cellular level. This method necessitates a major amount of manual effort, time, and the skill of pathologists. Furthermore, manual interpretation allows for the possibility of inter-observer variability, which might affect the consistency of diagnostic results

[3,4].

To overcome these issues in traditional methods, the recent clinical procedures have increasingly resorted to artificial-intelligence (AI) and deep-learning (DL), to automate the diagnosis process. Particularly, DL-methods have established better outcomes in the field of medical data analysis. DL-models have confirmed cutting-edge performance in tasks, such as HI classification, and segmentation during the cancer detection [5].

This study will use HI to apply lightweight DL (LDL) method for accurate and efficient BC detection. As a result of their decreased computational complexity, LDL models are particularly advantageous in medical applications. This makes it suitable for implementation in environments with restricted resources. The various phases in the proposed LDL-model based HI examination includes the following stages; HI collection form the chosen data repository and resizing it to 224x224 pixels, deep-feature extraction with the chosen LDL-model, classification and performance verification using SoftMax (SM) model, best model selection and generating the new feature vector using the fused/ensemble technique, and performance verification of the developed tool based on 3-fold cross-validation.

This work considered the LDL-schemes, like MobileNet-schemes and NASNet-schemes to propose a tool to detect the BC from the chosen HI-database. Initially, the performance is verified using the conventional-feature (CF) with SM and the best models are identified based on the achieved accuracy. These model features are then considered to generate the other feature vectors, like the fused-features (FF), and ensemble-features (EF) based on the guidelines provided in [6-8].

During this investigation, along with the SM-classifier, the approaches like, Random Forest (RF), Decision Tree (DT), K-Nearest Neighbour (KNN), and Support Vector Machine (SVM) are also considered and the achieved results are compared. The outcome of this study confirms that the CF based scheme provides the accuracy around >90% on the chosen LDL-models. The FF technique provides accuracy of >94% and the EF helps to achieve accuracy >98%. The detection result of RF achieved >98% accuracy when the EF is considered. This confirms that the considered LDL-model provides a better result on the chosen image database and helps to classify the chosen HI into benign/malignant case.

The contributions of this research include;

(i) Development of LDL-model based tool for benign/malignant BC detection using histopathology images,

(ii) Performance evaluation using CF, FF, and EF,

(iii) Verifying the model performance using classifiers, like SM, DT, RF, KNN, and SVM with 3-fold cross-validation

Other part of this work is organised as follows; Section 2 presents the literature review, Section 3 demonstrates the methodology, and Sections 4 and 5 shows result and conclusion of HI examination task.

2. LITERATURE REVIEW AND MOTIVATION

The cancer is one of the severe diseases in human community and reason for a large death rate globally. The BC is listed among the harsh cancers as per the recent report of the Global Cancer Observatory (GCO) and it is listed as the top cancer in women which causes a large occurrence and death rates [9,10].

The BC can be effectively diagnosed using various medical imaging schemes and the outcome of these approaches will help to detect the cancer and its severity to plan and execute the possible treatment procedure. Among all the medical imaging modalities, the BC detection based on HI plays a vital role in analysing the harshness of the BC in tissue level. Further, this finding will support for selecting the necessary treatment procedure to manage and cure the disease. Due to its significance, a number of AI-based examination methods are proposed to detect the BC using the chosen HI-database and the summary of few chosen methods are listed and discussed in Table 1. The proposed research is based on the motivation of the research work of Yang (2023) [11],

Table 1. Summary of HI-database BC detection procedure

Reference	Executed HI-data evaluation method
Niwas et al. [12]	This research considered the examination based on the complex wavelet attained texture feature to detect the disease and attained an accuracy of 87.8%
Araujo et al. [13]	This work considered the execution of a chosen DL-model to detect the BC in histology images and achieved 77.8% accuracy
Han et al. [14]	Histopathology based BC detection is presented with structured DL-

	model and obtained 93.4% accuracy.
Pan et al. [15]	Automatic segmentation and examination is presented using the histopathology images and it attained an accuracy of 92.2%
Roy et al. [16]	This research implemented patch-based examination of the histology images using the DL-model and achieved 87.4% accuracy
Sudharshan et al. [17]	This research executed multiple instance segmentation technique to detect the BC and it achieved an accuracy of 92.3%

From the discussion provided in Table 1, it can be noted that the DL-based BC detection is emerged as one of the major evaluation procedure for clinical data examination task. From the work of Yang (2023) [11], it can be noted that the HI-database BC examination provided a detection accuracy up to 94.83% when FF-based detection is executed using the KNN. The main limitation in the earlier work is, it considered the integration of the DL-feature with the machine-learning feature to achieve this result. Further, the earlier work considered the conventional DL-model, which has higher initial parameters to be tuned to implement the chosen classification task.

This work is planned the LDL-model based examination of the HI-data considered in Yang (2023). Further, the earlier work motivated to use the LDL to reduce the computation complexity in the earlier work without compromising the detection accuracy during the benign/malignant BC category. This work helped to achieve a detection result of >94% accuracy with FF and >98% accuracy with the EF attained using the considered procedures. The FF of this work is achieved using 50% feature dropout and serial concatenation of features of the best two models identified using the CF-based classification task. The EF-developed in this work is achieved based on the recent works discussed in [7,8]. Compared to the earlier research by Yang (2023) [11], this research achieved a better detection result with the LDL-models.

3. METHODOLOGY

The aims of this study are to propose an effective LDL-model based tool to examine the HI-database. Further, the chosen scheme must work with the real clinical images collected from the patient during the BC detection process. The developed BC detection scheme includes the two basic phases, in which phase1 presents the information regarding the data collection and preservation and phase2 provides the necessary procedures available in the developed LDL-tool to examine the chosen images to detect the benign/malignant BC.

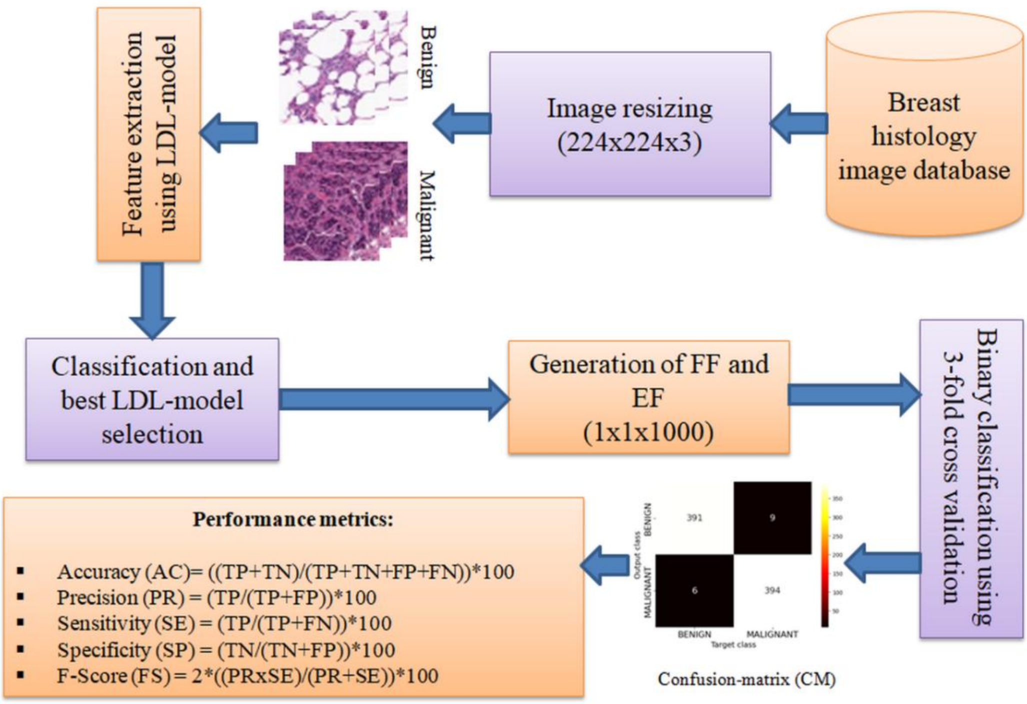


Figure 1. Proposed scheme to detect BC from histology slides

When the patient is diagnosed with the BC using traditional imaging procedure, then the biopsy collection and microscopy examination is then executed clinically. This process provided the Whole Slide Image (WSI). Examination of the WSI is quite complex and hence, image patch generation and evaluation is normally recommended by the researchers [18]. After generating the necessary patch, every patch is labelled based on the class and then stored in the data repository for further examination.

For the LDL-based examination, the labelled data available in the repository is collected and then resized to 224x224x3 pixels. The necessary features from these images are then extracted with the chosen LDL-model and then classified using the SM classifier. From the chosen MobileNet-variants [19,20] and NASNet-variants [21], the best models are selected based on the achieved classification accuracy and these model features are then chosen to generate the FF and EF. The outcome of the classification is the confusion-matrix (CM) with the necessary initial measures, like TP, TN, FP, and FN. From these values, the metrics like AC, PR, SE, SP, and FS are computed to verify the performance of the LDL-model based BC detection using HI-database.

Image database

Initially, the relevant images for the benign/malignant class histology examination are obtained from [22], and then they are resized to 224x224x3 pixels. In order to train and evaluate the performance of the developed DL-model, a total of 8000 image patches (4000 benign and 4000 malignant) are taken into consideration, as shown in Table 2. Sample test images that were taken into consideration for this study are depicted in Figure 2. The classification task is repeated 3-times with different data samples (3-fold) and the best outcome is recorded as final result.

Table 2.Test images used in this research

Class	Total images	Training	Testing	Validation
Benign	4000	3600	400	400
Malignant	4000	3600	400	400

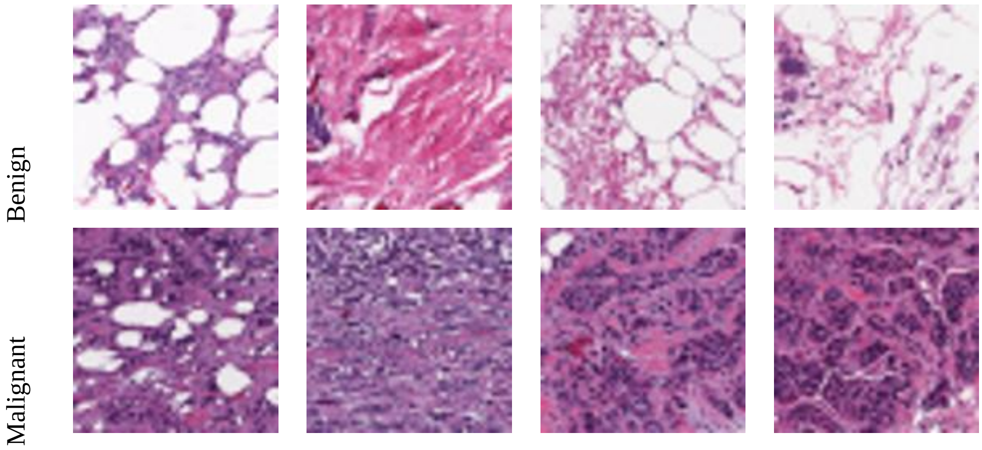


Figure 2. sample histology slides from the chosen image database

Deep Learning scheme

The DL-based medical data examination is commonly adopted by the researchers to achieve a better detection result based on the chosen task and the image database [23,24]. The earlier work confirms that the examination based on the pre-trained models provides agreeable outcome for a class of images including the histology slides [25]. Hence, this research considered the pre-trained LDL-models, like the MobileNet-variants and NASNet-variants for the study.

The MobileNet-variants, like MobileNetV1 (MNV1), MobileNetV1 (MNV2), MobileNetV3-Large (MNV3L), MobileNetV3-Small (MNV3S), NASNet-Mobile (NNM), and NASNet-Large (NNL) are considered in this research work. For every model, the following initial algorithm values are assigned; monitoring metric= accuracy and loss, Epochs= 100, learning rate= 1e-4, depth= 16, optimizer= Adam, pooling= max, activation= ReLU, and classifier= SoftMax. The detection task is executed using the 3-fold cross validation and the best outcome is recorded and analysed.

Feature vector generation

This work aims to develop a new feature vector from the traditional deep-features of dimension 1x1x1000; to achieve a better detection result during the benign/malignant classification. In this work, the FF and EF are generated and considered to implement the classification using the chosen models. The generation of FF involves in; considering the best two LDL-model (MNV1, and MNV3S) which provides a best detection accuracy during SoftMax based classification and executing 50% drop out from every model features. Then integrating these features serially to get the new FF with dimension 1x1x1000 (ie. 1x1x500 and 1x1x500 gets the 1x1x1000 after serial integration). This feature is then considered to verify the performance of the developed tool.

To generate the EF-vector, the work proposed in the literature is adopted [7,8]. Based on the earlier result during the SoftMax classification, this research considered the three best LDL-models (MNV1, MNV2 and MNV3S) to obtain the necessary feature vector. During this task, the accuracy is chosen as the performance metric and the best feature from every model is then considered to generate the EF with dimension 1x1x1000.

The necessary feature vector of FF (1x1x1000) and EF (1x1x1000) are then considered to detect benign/malignant BC using the classifiers, like Decision-Tree (DT), random-Forest (RF), K-Nearest Neighbour (KNN), and Support Vector Machine (SVM), as discussed in the earlier research works [26].

Performance evaluation and verification

Implementation of the suggested LDL-scheme is carried out, and the results are then documented and analyzed using the Python software. This work considered a computer having Inteli5 processor, 20GB of RAM), and 4GB of VRAM for investigation.
This work considered the initial measures like TP, FN, TN, and FP from CM for the examination. Additionally, metrics such as AC, PR, SE, SP, and FS are also computed in order to obtain the results. The necessary information about these values can be found in [27].

4. RESULT AND DISCUSSION

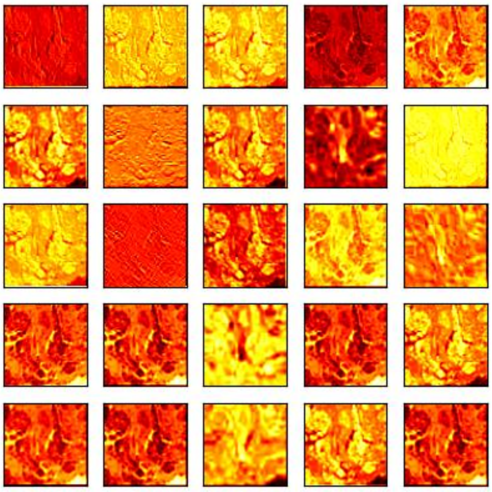
This section of the research presents the experimental outcome and its discussions on the chosen LDL-model. The achieved results are presented and discussed to demonstrate the performance of the developed BC detection process.

Initially, the benign/malignant BC detection task is executed using the MNV1 classifier with the SoftMax (SM) classifier and the achieved result for 3-fold cross-validation is recorded and analysed. This process provided a test accuracy of 92.5% on the chosen HI-database. The convolutional layer results for the chosen image are shown in Figure 3 which confirms that the pixel to feature conversion procession is smooth in this process. Fig 3(a) to (d) depicts four convolutional outcomes for a chosen malignant image.

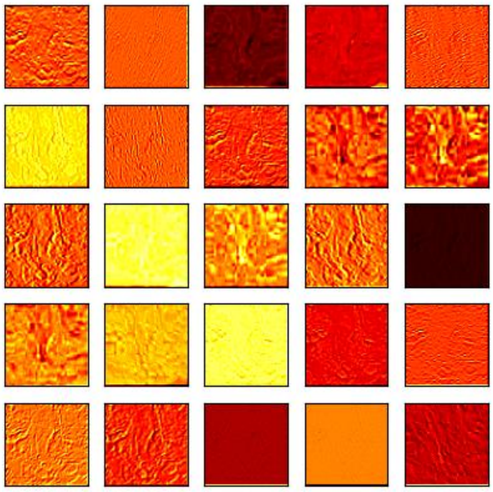
Similar process is repeated with other chosen LDL-models and the achieve outcome is recorded as in Table 3. This table confirms that the MNV3S achieved a best accuracy of 92.75% compared to other models. Further, MNV1 (92.5%) and MNV2 (92.125%) also attained better outcomes compared to MNV3L, NNM, and NNL models as in Table 3. For the FF generation, MNV3S and MNV1 model features are considered after a 50% dropout and this FF is then considered to verify the BC detection task with chosen classifiers. Similarly MNV1, MNV2, and MNV3S models are considered to generate the EF vector and the classification is repeated.

The performance of LDL-model with the classifiers, like DT, RF, KNN, and SVM are verified with FF/EF. The Experimental outcome (train/validate) achieved with FF and RF is shown in Figure 4. Fig 4(a) shows accuracy and Fig 4(b) presents the loss and these images confirm that the RF helps to achieve a better outcome for a chosen epoch size of 100. The final outcome achieved with this task is shown in Figure 5. Fig 5(a) shows the CM and Fig 5(b) presents the ROC-curve. These images confirms that the experimental outcome of this classification is better with the RF for FF.

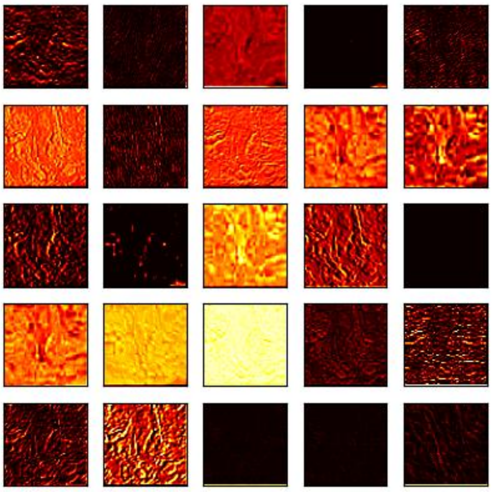
Similar procedure is repeated with the EF and the final outcome achieved is recorded as in Table 4. This table confirms that, the RF based detection provides >98% accuracy for both FF and EF and this confirms that the proposed technique works well on the chosen database. Compared to the earlier work of Yang [11] which considered the similar image database, the proposed LDL-model provides an improved accuracy, which confirms the significance of the proposed scheme for the chosen HI-database. In the future, the proposed scheme can be considered to examine the clinical grade images to detect the BC with better accuracy.



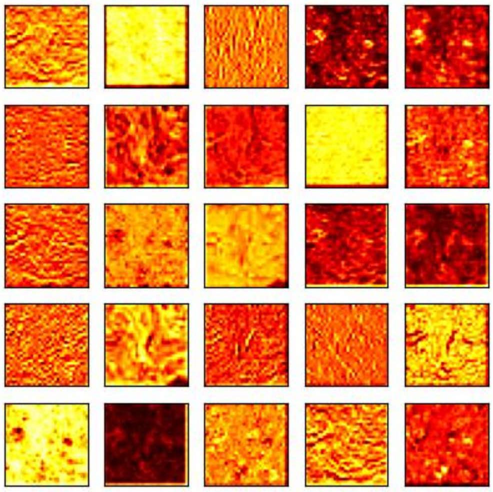
(a) Convolution1



(b) Convolution2



(c) Convolution3

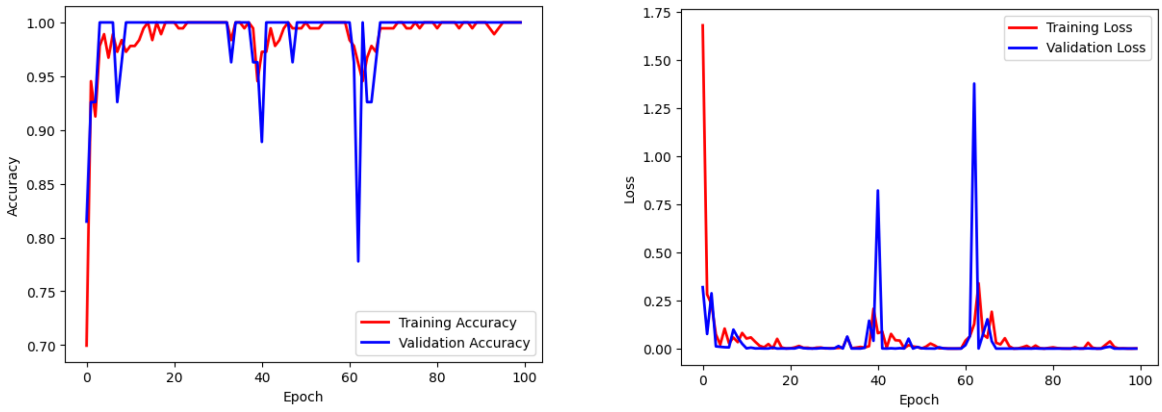


(d) Convolution4

Figure 3. Various convolution result attained using MNV1

Table 3. Experimental outcome attained with LDL-model and SoftMax classifier

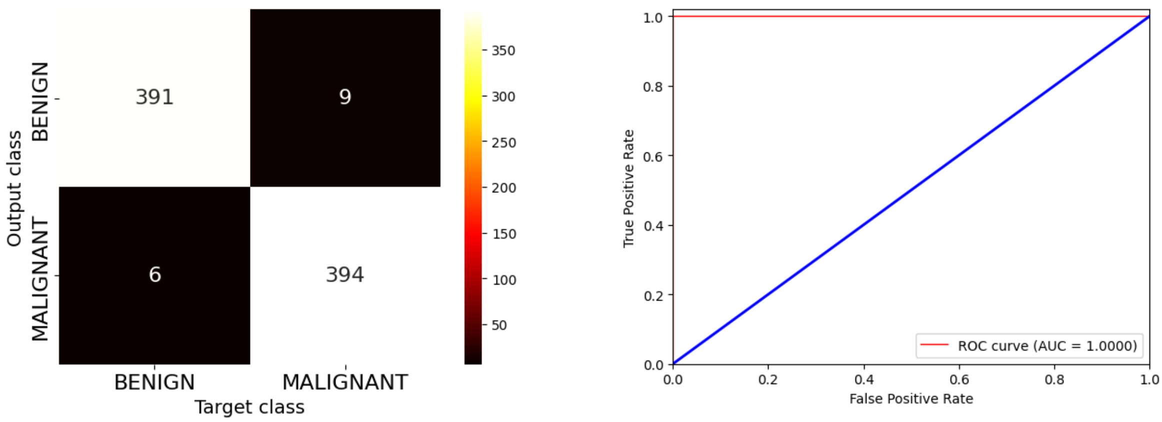
Model	**TP**	**FN**	**TN**	**FP**	**AC**	**PR**	**SE**	**SP**	**FS**
MNV1	364	36	376	24	92.5000	93.8144	91	94	92.3858
MNV2	367	33	370	30	92.1250	92.4433	91.7500	92.5000	92.0954
MNV3S	369	31	373	27	92.7500	93.1818	92.2500	93.2500	92.7136
MNV3L	362	38	372	28	91.7500	92.8205	90.5000	93	91.6456
NNM	366	34	365	35	91.3750	91.2718	91.5000	91.2500	91.3858
NNL	368	32	361	39	91.1250	90.4177	92	90.2500	91.2020



(a) Accuracy Vs Epoch

(b) Loss Vs Epoch

Figure 4. training and validation result with FF and RF classifier



(a) CM

(b) ROC-curve

Figure 5. Binary classification result with the FF and RF classifier

Table 4. Experimental outcome attained with FF/EF with chosen binary classifiers

Feature	Model	TP	FN	TN	FP	AC	PR	SE	SP	FS
FF	DT	386	14	392	8	97.2500	97.9695	96.5000	98	97.2292
	RF	394	6	391	9	98.1250	97.7667	98.5000	97.7500	98.1320
	KNN	392	8	388	12	97.5000	97.0297	98	97	97.5124
	SVM	394	6	387	13	97.6250	96.8059	98.5000	96.7500	97.6456
EF	DT	389	11	390	10	97.3750	97.4937	97.2500	97.5000	97.3717
	RF	392	8	393	7	98.1250	98.2456	98	98.2500	98.1227
	KNN	394	6	388	12	97.7500	97.0443	98.5000	97	97.7667
	SVM	391	9	392	8	97.8750	97.9950	97.7500	98	97.8723

5. CONCLUSION

BC is one of the harsh diseases in women community and early detection and treatment is vital to reduce its harshness. The clinical level detection is commonly performed using the HI and hence, this work proposed LDL-based scheme to examine the chosen HI labelled as benign/malignant class. This work considered the MN-variants and NN-variants for the LDL scheme development and the proposed investigation is executed using the FF and EF. This work initially executed the classification using SoftMax. Then, the common classifiers, like DT, RF, KNN, and SVM are considered. The experimental outcome of this study confirms that the proposed FF/EF based bc detection achieved an accuracy >98% on the chosen model, which confirms that the implemented technique provides a better detection compared to other similar results found in the literature. In the future, this model can be considered to examine the clinical grade BC data collected from real patients.

REFERENCES

[1] Roheel, A., Khan, A., Anwar, F., Akbar, Z., Akhtar, M. F., Imran Khan, M., ... & Ahmad, R. (2023). Global epidemiology of breast cancer based on risk factors: a systematic review. Frontiers in Oncology, 13, 1240098.

[2] Cao, S., Wei, Y., Huang, J., Yue, Y., Deng, A., Zeng, H., & Wei, W. (2024). A bibliometric worldview of breast-conserving surgery for breast cancer from 2013 to 2023. Frontiers in Oncology, 14, 1405351.

[3] Gurcan, M. N., Boucheron, L. E., Can, A., Madabhushi, A., Rajpoot, N. M., & Yener, B. (2009). Histopathological image analysis: A review. IEEE reviews in biomedical engineering, 2, 147-171.

[4] Elazab, N., Soliman, H., El-Sappagh, S., Islam, S. R., & Elmogy, M. (2020). Objective diagnosis for histopathological images based on machine learning techniques: Classical approaches and new trends. Mathematics, 8(11), 1863.

[5] Zhao, Y., Zhang, J., Hu, D., Qu, H., Tian, Y., & Cui, X. (2022). Application of deep learning in histopathology images of breast cancer: a review. Micromachines, 13(12), 2197.

[6] Kaur, A., Kaushal, C., Sandhu, J. K., Damaševičius, R., & Thakur, N. (2023). Histopathological image diagnosis for breast cancer diagnosis based on deep mutual learning. Diagnostics, 14(1), 95.

[7] Rajaram, G., Rajinikanth, V., & Latha, B. S. (2024, August). Classification of Breast Histology into Benign and Malignant using ResNet-Variants: A Study with BreakHis Database. In 2024 9th International Conference on Applying New Technology in Green Buildings (ATiGB) (pp. 479-483). IEEE.

[8] Rajinikanth, V., Biju, R., Mittal, N., Mittal, V., Askar, S. S., & Abouhawwash, M. (2024). COVID-19 detection in lung CT slices using Brownian-butterfly-algorithm optimized lightweight deep features. Heliyon, 10(5).

[9] Bray, F., Laversanne, M., Sung, H., Ferlay, J., Siegel, R. L., Soerjomataram, I., & Jemal, A. (2024). Global cancer statistics 2022: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA: a cancer journal for clinicians, 74(3), 229-263.

[10] https://gco.iarc.fr/en

[11] Yang, Y. (2023). Automatic Screening System to Distinguish Benign/Malignant Breast-Cancer Histology Images Using Optimized Deep and Handcrafted Features. International Journal of Computational Intelligence Systems, 16(1), 138.

[12] Niwas, S. I., Palanisamy, P., & Sujathan, K. (2010, July). Complex wavelet based texture features of cancer cytology images. In 2010 5th International Conference on Industrial and Information Systems (pp. 348-353). IEEE.

[13] Araújo T, Aresta G, Castro E, Rouco J, Aguiar P, Eloy C, Polónia A, Campilho A (2017) Classifcation of breast cancer histology images using convolutional neural networks. PloS One 12(6):e0177544

[14] Han Z, Wei B, Zheng Y, Yin Y, Li K, Li S (2017) Breast cancer multi-classifcation from histopathological images with structured deep learning model. Sci Rep 7(1):4172

[15] Pan X, Li L, Yang H, Liu Z, Yang J, Zhao L, Fan Y (2017) Accurate segmentation of nuclei in pathological images via sparse reconstruction and deep convolutional networks. Neurocomputing 229:88–99

[16] Roy K, Banik D, Bhattacharjee D, Nasipuri M (2019) Patchbased system for classifcation of breast histology images using deep learning. Comput Med Imaging Graph 71:90–103

[17] Sudharshan P, Petitjean C, Spanhol F, Oliveira LE, Heutte L, Honeine P (2019) Multiple instance learning for histopathological breast cancer image classification. Exp Syst Appl 117:103–111

[18] Rehman, Z. U., Ahmad Fauzi, M. F., Wan Ahmad, W. S. H. M., Abas, F. S., Cheah, P. L., Chiew, S. F., & Looi, L. M. (2024). Deep-Learning-Based Approach in Cancer-Region Assessment from HER2-SISH Breast Histopathology Whole Slide Images. Cancers, 16(22), 3794.

[19] Mohan, R., Damasevicius, R., Taniar, D., Raja, N. S. M., & Rajinikanth, V. (2024, March). Automatic Monkeypox Disease Detection from Preprocessed Images using MobileNetV2. In 2024 Tenth International Conference on Bio Signals, Images, and Instrumentation (ICBSII) (pp. 1-4). IEEE.

[20] Ansar, W., Shahid, A. R., Raza, B., & Dar, A. H. (2020). Breast cancer detection and localization using mobilenet based transfer learning for mammograms. In Intelligent Computing Systems: Third International Symposium, ISICS 2020, Sharjah, United Arab Emirates, March 18–19, 2020, Proceedings 3 (pp. 11-21). Springer International Publishing.

[21] Alruwaili, M., & Gouda, W. (2022). Automated breast cancer detection models based on transfer learning. Sensors, 22(3), 876.

[22] https://www.kaggle.com/datasets/paultimothymooney/breast-histopathology-images

[23] Mohan, R., Rama, A., Raja, R. K., Shaik, M. R., Khan, M., Shaik, B., & Rajinikanth, V. (2023). OralNet: fused optimal deep features framework for oral squamous cell carcinoma detection. Biomolecules, 13(7), 1090.

[24] Vijayakumar, K., Maziz, M. N. H., Ramadasan, S., Prabha, S., & Kumaar, K. S. N. (2024, May). Automatic Classification of Healthy/TB Chest X-ray using DeepLearning. In 2024 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI) (pp. 1-5). IEEE.

[25] Ramadasan, S., Saranya, S., Vijayakumar, K., Prabha, S., Dutta, P. K., & Singh, S. K. (2024, October). Deep-Learning and Geometric Mean Optimizer Combined Scheme for Brain MRI Classification. In 2024 IEEE 12th Region 10 Humanitarian Technology Conference (R10-HTC) (pp. 1-6). IEEE.

[26] Kadry, S., Crespo, R. G., Herrera-Viedma, E., Krishnamoorthy, S., & Rajinikanth, V. (2023). Classification of breast thermal images into healthy/cancer group using pre-trained deep learning schemes. Procedia Computer Science, 218, 24-34.

[27] Vijayakumar, K., Maziz, M. N. H., Ramadasan, S., Balaji, G., & Prabha, S. (2024, May). Benign/Malignant Skin Melanoma Detection from Dermoscopy Images using Lightweight Deep Transfer Learning. In 2024 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI) (pp. 1-5). IEEE...

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