

Detection of breast cancer with ensemble learning using magnetic resonance imaging

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ABSTRACT

Despite notable progress in medicine along with technology, the deaths due to breast cancer are increasing steadily. This paper proposes a framework to aid the early detection of lesions in breast with magnetic resonance imaging (MRI). The work has been carried out using diffusion weighted imaging (DWI) and dynamic contrast enhanced-magnetic resonance imaging (DCE-MRI). Data augmentation has been incorporated to enlarge the data set collected from a reputed hospital. Deep learning has been implemented using the ensemble of convolutional neural network (CNN). Amongst the individual CNN models, the you only look once (YOLO) CNN yielded the highest performance with an accuracy of 93.4%, sensitivity of 93.44%, specificity of 93.33%, and F1-score of 93.44%. Using Hungarian optimization, appropriate selection of individual CNN architectures to form the ensemble of CNN was possible. The ensemble model enhanced performance with 95.87% accuracy, 95.08% sensitivity, 96.67% specificity, and F1-score of 95.87%.

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1. INTRODUCTION

The number of individuals detected with breast cancer as well as the number of deaths resulting from it are on the rise. In 2021, in the United States of America (USA), the number of breast cancer patients was approximately 0.4 crores [1]. In India, detecting the disease at an advanced stage is one of the most frequent factors contributing to the high death rate, and it can be because of inadequate knowledge, unfinished treatment plans, and restricted availability of efficient care at rural cancer centers [2].

In the initial stages of breast cancer, there may not be any symptoms observed. Variable shapes, positions, and dimensions make the detection difficult. This research suggests a deep-learning approach for the detection of breast lesions using magnetic resonance imaging (MRI). Artificial intelligence has not evolved to the extent that it can be independently used for medical considerations but may be used to assist medical practitioners [3]. Systems utilizing deep learning algorithms for have been implemented to help doctors. The complexity of the system is low.

Deep convolutional neural network (CNN) assists in detecting and categorizing lesions using image analysis [4]. Khan *et al.* [5] proposed a model, where prediction was done by fusing the features extracted by CNN from four views of mammograms into one layer and achieved an accuracy of 92.29%. Wang *et al.* [6] fused the density features, texture features, and morphological features to boost the accuracy of the CNN model. To excerpt features, Zhang *et al.* [7] employed univariate and multivariate logistic regression

evaluations for multiparametric breast MRI. Parekh *et al.* [8] developed a system using SSAE for multiparametric breast MRI. However, their system faced the drawback that it needed exhaustive computations.

Gullo *et al.* [9] emphasized that the training of the deep learning models ought to be done on massive and diversified datasets to have accurate detection. Aurna *et al.* [10] merged two datasets and achieved the generality of their work on MRI brain tumors using CNN. According to Saleh *et al.* [11] the deep recurrent neural network (RNN) that was optimized using the univariate technique and features that were chosen performed the best. Muduli *et al.* [12] stated that by choosing the samples equally from each class, the problem of imbalance in classes can be avoided.

The dissimilarity of the classifiers can be utilized to enhance the classification performance by employing ensemble learning [13]. To describe it in simpler terms, an ensemble model leads to predictions that are more accurate compared to those of a single model by combining multiple of them. In Ensemble learning, the resultant prediction of the ensemble is obtained by using averaging of the predictions of selected CNN models or by using voting. In voting, either the majority is considered or weighted output is evaluated [14]. Hungarian optimization ensures the optimal selection of classifiers for the ensemble [15].

2. METHOD

This section describes the details of data acquisition. A brief overview of the CNN architectures used follows. The proposed methodology is discussed later in this section.

2.1. Data acquisition

Several imaging techniques are available for the identification of breast cancer. MRI is a non-invasive imaging technology. Small lesions whose measure is lower than 1 cm may not necessarily be detected by breast ultrasound [16]. The sensitivity of combination screening, according to the researchers, was 96.2%, compared to 79.7% with MRI and 48.1% with mammography [17]. MRI may minimize unnecessary biopsies [18].

According to our review, the rising trend of DCE-MRI utilization has been observed in recent years [19]. A section of inflated gray intensity appears in the DCE-MRI because the unusual tissues absorb higher contrast agents in comparison with the usual tissues. Diffusion weighted imaging (DWI), when combined with dynamic contrast-enhanced MRI (DCE-MRI), boosts the system's performance.

MRI scans namely DCE-MRI and DWI were chosen as the input to our system after analyzing all these aspects. The MRI images are available in the digital imaging and communications in medicine (DICOM) format. The RadiAnt DICOM Viewer is downloaded to view MRI images. A specimen of the cancerous and benign images is displayed in Figures 1(a) and 1(b) respectively. Data collection for our research has been done from a reputed hospital, namely Nanavati Max Super Specialty Hospital, Mumbai.

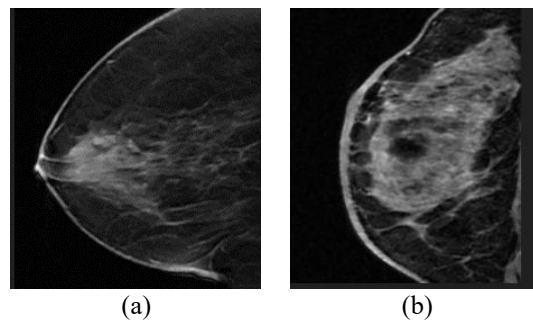


Figure 1. MRI images (a) sample of malignant images and (b) sample of malignant images

2.2. CNN architectures

With the increase in research in artificial intelligence and better computing facilities, the use of CNN in medical imaging has increased extensively. Contrary to traditional machine learning algorithms requiring manual feature extraction, CNN can perform feature extraction. CNN models' weight-sharing ability and sparse connectivity reduce training times and costs.

The pre-trained models and the knowledge acquired can be used in the process of transfer learning, thus eliminating the requirement for enormous volumes of data. The CNN architectures that were implemented in our research were DenseNet-201, MatConvNet, VGGNet, Inception-V3, AlexNet, and you

only look once (YOLO) CNN. The choice of CNN was established on our analysis results in [15]. The selected CNN models were computationally efficient and satisfactorily executed using one graphical processing unit (GPU). This minimal complexity makes the system a potential solution at rural areas.

2.2.1. DenseNet-201

Each layer's output in the DenseNet model is linked to the following layer to promote feature reuse. The DenseNet model comprises different modules such as DenseBlock, composite layer, transition layer, and growth rate. Lesions of different dimensions could be possibly detected by extraction of Low-level and intermediate-level features using DenseNet CNN [20]. DenseNet-201 has 201 layers with almost 20 million parameters.

2.2.2. Inception-V3

The inception net architecture has 48 layers with 24 million parameters. GoogLeNet is another name for Inception-V3. An inception module has the potential to extract multi-level features. The Inception module led to a depletion in network parameters.

2.2.3. MatConvNet

MATLAB functions enable the building of CNN models which have good adaptability [21]. MatConvNet allows fast prototyping of fresh CNN architectures. Complex models may be built on large datasets with MatConvNet's effective execution on GPU and central processing unit (CPU).

2.2.4. YOLO

In you only look once (YOLO) CNN, bounding box locations and class probabilities are found simultaneously by building a single network to handle object recognition as a regression [22]. The architecture of YOLO-V2 CNN used in our project is illustrated in Figure 2. As a result, YOLO CNN can detect objects quickly. One major benefit of YOLO is its capacity to generalize across multiple images. Rectangular areas of interest (ROI) for tumors were labeled. YOLO-V2 uses a single neural network pass to accomplish detection. YOLO-V2 removes the need for complex components like region proposal networks and multi-stage training, streamlining the architecture for easier implementation and faster deployment in production environments.

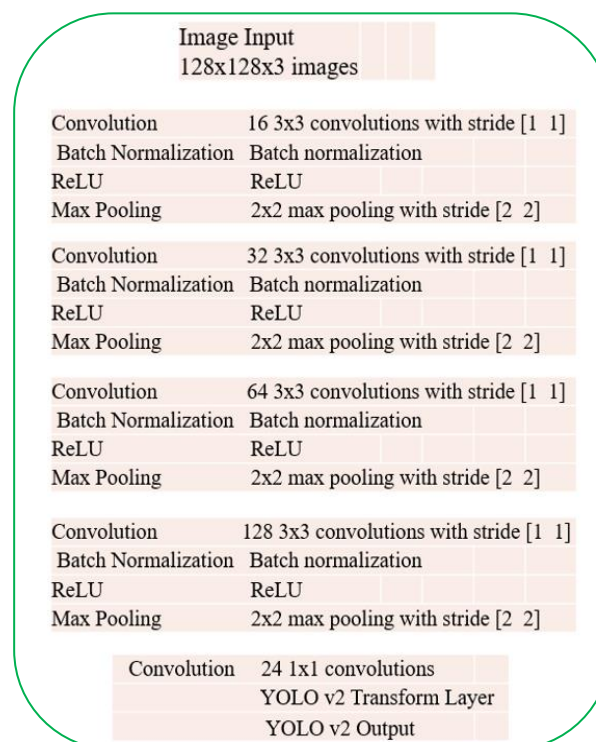


Figure 2. YOLO-V2 CNN architecture

2.2.5. AlexNet

Krizhevsky *et al.* [23] presented a CNN model named AlexNet, which has eight layers and is the first CNN in history to mark the turn of researchers' attention back to deep learning. AlexNet's deep architecture comprises several convolutional, pooling, and fully connected layers and has 60 million parameters. The architecture enables it to learn complex features.

2.2.6. VGG-19

The visual graphics group (VGG) developed the VGGNet model. An increase in the depth of the network was introduced to improve accuracy. In our research, VGG-19 is implemented which has 19 layers. The increasingly widespread use of VGG-19 can be attributed to its strong feature extraction capabilities.

2.3. Methodology

Figure 3 represents the process flow diagram of our proposed approach. The blocks in our proposed model include data acquisition, data processing, ensemble learning, and output. Since data acquisition has been discussed previously, the rest of the blocks are discussed in the next subsections. A brief description about the hardware and software requirements is presented.

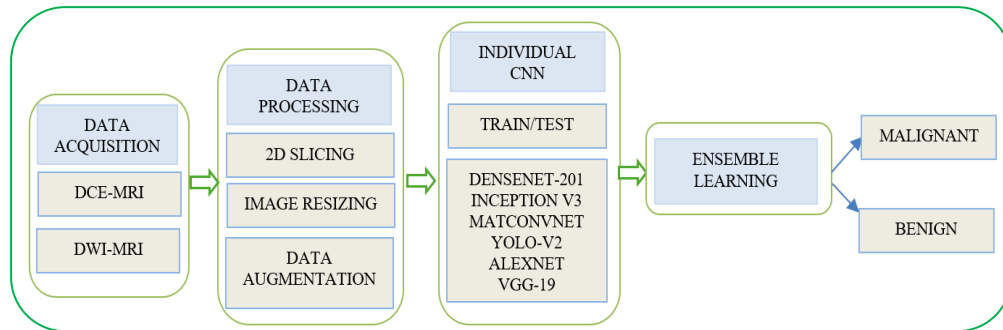


Figure 3. Process flow diagram of our proposed approach

2.3.1. Data processing

3D CNN models were not implemented considering their high computational complexity. 2D CNN architectures cannot be utilized directly with MRI inputs as the data is three-dimensional. Since the MRI data is in the 3D format, the 3D MRI data was manually sliced to obtain 2D MRI images. The first few and last few frames were not included in the sampling, as there was less information in those frames. The sampling was done randomly. The sampling was manually done to capture the frames having relevant information. The input sizes may differ depending on the CNN model. Images can be easily resized to a square shape to ensure that their width and height are the same, which makes the process of handling data easier. The MRI input samples were rescaled to match the dimensions of the CNN input. Models may adapt better generalization to new data using data augmentation. Data augmentation is significant when there is a lack of ground-truth data or when gathering natural data is time-consuming or costly. Overfitting is lowered by data augmentation. Expansion of the magnitude of the dataset, data augmentation using various operations like flipping and rotation is incorporated. The data augmentation increased the magnitude of the data by eight folds.

2.3.2. Hardware and software requirements

The implementation of our project is done using an Intel Core i7 Processor, RAM of 8 GB, Nvidia GeForce GTX 1650 Ti GPU and 1 TB harddisk. An optimal environment enabling deep learning using training models and deployment is offered by MATLAB. Our project was executed using the deep learning toolbox from MATLAB R2022a installed on Windows 11. Deep learning toolbox enables the implementation of pre-trained CNN models.

2.3.3. Ensemble model of CNN

The ensemble model of three CNN classifiers was implemented to boost performance. The steps involved in developing ensemble learning are illustrated in Figure 4. Independent CNN models are trained followed by testing them. Merging the predictions from several CNN increases the overall accuracy by decreasing the possibility of errors. Ensembles perform better on unseen or noisy data because they are less

prone to overfit the training set. Ensembles average out the errors made by individual CNN models, producing more reliable predictions.

The majority voting algorithm has been incorporated into ensemble learning. This method is also called hard voting and is robust despite being straightforward. With each base classifier model, an input is given, and an output class label is predicted. The most frequent category label among individual predictions decides the final ensemble prediction. Assignment problems will always have an ideal solution in response to the Hungarian algorithm. According to the nature of the problem, the objective function value or total cost is either maximized or minimized. Hungarian optimization is used to choose the CNN models having the highest performance to form the ensemble. The foundation of the Hungarian method is the idea that the optimum solution to the resultant assignment problem is the same as the problem itself and vice versa if a constant is added to each element of a row and column of the cost matrix. Majority voting is incorporated to yield the final output.

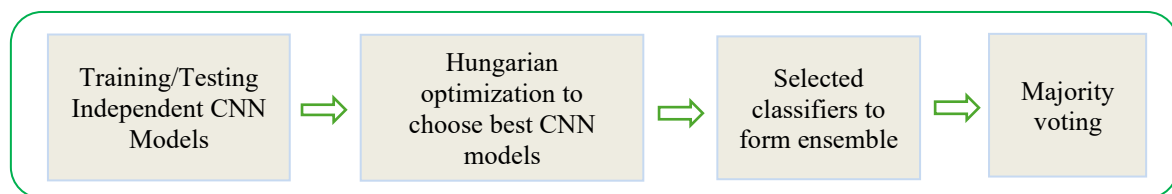


Figure 4. Schematic diagram for ensemble learning

2.3.4. Output block

Dual classification and multiple-class classification are two fundamental types of classification. Based on a given collection of labeled examples, a binary classifier is a form of classification technique that estimates binary labels (*e.g.*, -1 or 1) for any newly unseen examples. It builds a classifier that gives a new data point one of two possible labels.

3. RESULTS AND DISCUSSION

The selection of hyperparameters is a crucial step in designing deep learning models. To improve training, batch normalization can reduce a model's sensitivity to its starting weights. A batch size of thirty-two was used to implement batch normalization. The training-testing ratio was set at 70:30. At 0.001, the learning rate was kept constant.

To force the remaining neurons in a layer to learn more robust features, dropout operates by randomly eliminating a portion of the neurons in the layer during training. As a result, there is less co-dependency between neurons and no chance of one of them updating the errors of another. Dropout lowers overfitting and enhances generalization abilities. This helps us get better results on datasets that have not been seen before. The dropout factor was maintained at 0.5.

The experimentation was done using 10 epochs and applying the Backpropagation algorithm. Adaptive moment estimation (ADAM), a variant of Stochastic gradient descent, was used for parameter updating in training. ADAM uses less memory and is a computationally efficient optimizer.

The individual CNN architectures were model fitted with the MRI dataset, having 120 benign samples and 122 malignant samples. The performance evaluation was done based on the true negatives, true positives, false positives, and false negatives values that were computed from the confusion matrices. The performance evaluation was done using the metrics namely sensitivity, accuracy, specificity, and F1-score. The clinical significance of the metrics is discussed below.

Sensitivity is a system's ability to correctly identify patients with a disease. The term Specificity is a system's ability to correctly sort persons without illness. False negatives and false positives are viewed similarly in accuracy. Misclassifying some cases may have variable implications based on the nature of the situation. Particularly in the diagnosis of a disease, a false negative might be more dangerous in comparison with a false positive. Accuracy can be deceptive in situations when one class exceeds the others. A model could, for instance, predict just the majority class and still have a high accuracy rating. However, the F1-score will accurately represent the model's performance in every class. The model's capacity to accurately identify positive patients while minimizing false positives and false negatives is evaluated fairly by the F1-score.

This research is done to help radiologists in making faster decisions. This system is proposed to aid the patients especially in rural areas where there is a scarcity of expert radiologists. It facilitates decision-making and offers precise insights, which lowers expenses and difficulties. The performance of the CNN models is summarized in Table 1.

The performance metrics considered for the Hungarian optimization were sensitivity, specificity, and F1-Score. All the elements were normalized between 0 and 1 and later negated to maximize the total cost. Table 2 represents the optimal cost matrix resulting from Hungarian optimization. The optimal value obtained is 2.9344.

According to the optimization results, the individual CNN models that outperform the other CNN models are YOLO, MatConvNet, and AlexNet, which are chosen to form the ensemble. Ensemble learning employs majority voting. The simulation results comprising of confusion matrix and receiver operating characteristic (ROC) curve are shown in Figures 5(a) and 5(b) respectively. The performance metrics of the proposed ensemble system are shown in Table 3. An impact analysis is done to check the improvement in performance due to the application of the Hungarian optimization to form the ensemble. The mean performance metrics with the various CNN models are evaluated and compared with the performance metric achieved by the ensemble model. Table 3 illustrates the performance improvement. The performance achieved by introducing the ensemble is far superior to that of individual CNN models. Considering the percentage improvement in the accuracy metric, since the p-value is much less than 0.05, the improvement is statistically significant at the 95% confidence level. The confidence intervals do not coincide, which further supports that the difference is statistically meaningful.

Table 1. The performance of CNN models

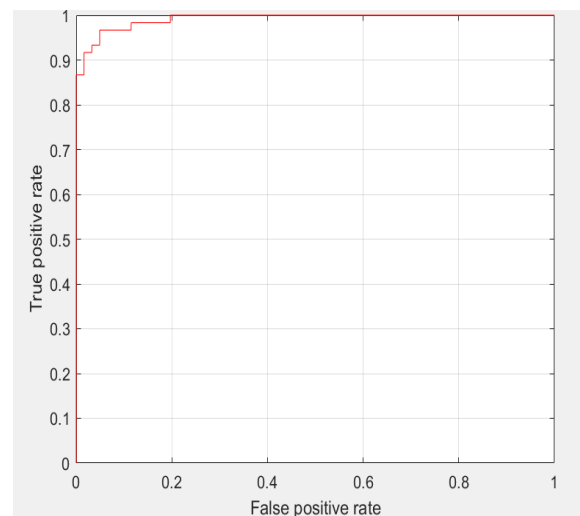
CNN model	Sensitivity	Specificity	F1-Score	Accuracy
DenseNet-201	0.9508	0.7666	0.8720	0.8600
Inception-V3	0.9344	0.8666	0.9048	0.9010
MatConvNet	1.0000	0.8333	0.9231	0.9170
VGG-19	0.7213	0.9833	0.8302	0.8510
AlexNet	0.7213	1.0000	0.8380	0.8600
YOLO	0.9344	0.9333	0.9344	0.9340

Table 2. The optimal cost matrix

CNN Model	Sensitivity	Specificity	F1-Score
DenseNet-201	0.9508	0.7666	0.8720
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VGG-19	0.7213	0.9833	0.8302
AlexNet	0.7213	1.0000	0.8380
YOLO	0.9344	0.9333	0.9344



(a)



(b)

Figure 5. The simulation results (a) confusion matrix and (b) the ROC curve

Table 3. The performance improvement analysis of the proposed ensemble system

Performance metric	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)
Individual CNN average	88.72	87.70	89.72	88.38
Proposed ensemble model	95.87	95.08	96.67	95.87
Improvement	7.15	7.38	6.95	7.49

The proposed ensemble system is contrasted with other existing systems with regards of accuracy, as shown in Table 4. The research work done only on MRI data was considered. The methods implemented and the dataset used are specified. The data presented in the tables shows that the proposed ensemble system surpassed the existing models, proposed by other researchers.

Table 4. Comparison of the ensemble system with existing systems

Reference	Accuracy (%)	Method	Dataset	Year
Sun <i>et al.</i> [24]	92.37	Cross-attention multi-branch net	DCE-MRI	2023
Abdullah <i>et al.</i> [25]	90.00	CNN	Multiparametric MRI	2025
Zheng <i>et al.</i> [26]	82.40	PCMM – Net	Multiparametric MRI	2024
Ashfaq <i>et al.</i> [27]	90.57	CNN	MRI	2022
Proposed ensemble model	95.87	Ensemble of CNN	DCE-MRI, DWI	2025

4. CONCLUSION

The proposed computer-aided design technique utilizes the multiparametric MRI data by exploiting the additional information presented by DCE-MRI and DWI-MRI for the breast tumors detection. The data was gathered from Nanavati Max Super Speciality Hospital. Dropout and data augmentation were employed to avoid overfitting. Experimentation was done independently using CNN. The accuracies achieved by DenseNet-201, Inception-V3, MatConvNet, VGG-19, AlexNet and YOLO CNN are 0.86, 0.901, 0.917, 0.851, 0.86, and 0.934 respectively. The YOLO CNN could attain the topmost accuracy of 93.4% compared with the other CNN models.

Following the experimentation with individual CNN models, the results were optimized using Hungarian optimization for choosing the best CNN models to form the ensemble. The ensemble system significantly outperformed the individual CNN models and other existing systems with an accuracy of 95.87%. The percentage improvement in the Accuracy metric with the ensemble model over the average of individual CNN models is 7.15%, which is statistically significant.

5. LIMITATIONS AND FUTURE WORK

A limitation is that the sampling was manually done to capture the frames. Sampling can be automated. In case computational resources are available, 3D CNN models can be implemented in future. Future work could involve detection and classification by fetching data from multiple hospitals. The data from various modalities like mammograms along with MRI can be considered. Also, other sequences like T1-weighted, and T2-weighted MRI sequences may be applied.

Since, CNN models rely on vast amounts of data, there is a wide scope for researchers to collect the data, clean and label it. Further machine learning algorithms could be combined with CNN models. The other computationally hungry CNN models can be used for improvisation in performance.

The minority class may be assigned biased weights as there are imbalanced classes. Work can be done for noise removal with low-quality, noisy, or poorly preprocessed images. The integration of CNN into current clinical workflows requires validation, approvals and physician training. AI driven diagnosis raises additional ethical and legal issues, which need to be addressed to ensure the project to be actually implemented in true sense.

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REFERENCES

- [1] B. Sathiyabhama *et al.*, "A novel feature selection framework based on grey wolf optimizer for mammogram image analysis," *Neural Computing and Applications*, vol. 33, no. 21, pp. 14583–14602, Nov. 2021, doi: 10.1007/s00521-021-06099-z.
- [2] S. P. Somashekhar *et al.*, "Association of breast surgeons of India (ABSI) practical consensus statement, recommendations, and guidelines for the treatment of breast cancer in India 2021—Indian solutions for Indian problems," *Indian Journal of Surgery*, vol. 84, no. S3, pp. 573–584, Oct. 2022, doi: 10.1007/s12262-021-03160-y.
- [3] S. M. Ryu *et al.*, "Automated landmark identification for diagnosis of the deformity using a cascade convolutional neural network (FlatNet) on weight-bearing lateral radiographs of the foot," *Computers in Biology and Medicine*, vol. 148, p. 105914, Sep. 2022, doi: 10.1016/j.combiomed.2022.105914.
- [4] J. Iqbal *et al.*, "Reimagining healthcare: unleashing the power of artificial intelligence in medicine," *Cureus*, vol. 15, no. 9, Sep. 2023, doi: 10.7759/cureus.44658.
- [5] H. Nasir Khan, A. R. Shahid, B. Raza, A. H. Dar, and H. Alquhayz, "Multi-view feature fusion based four views model for mammogram classification using convolutional neural network," *IEEE Access*, vol. 7, pp. 165724–165733, 2019, doi: 10.1109/ACCESS.2019.2953318.
- [6] Z. Wang *et al.*, "Breast cancer detection using extreme learning machine based on feature fusion With CNN deep features," *IEEE Access*, vol. 7, pp. 105146–105158, 2019, doi: 10.1109/ACCESS.2019.2892795.
- [7] J. Zhang *et al.*, "Multiparametric MRI-based radiomics nomogram for preoperative prediction of lymphovascular invasion and clinical outcomes in patients with breast invasive ductal carcinoma," *European Radiology*, vol. 32, no. 6, pp. 4079–4089, Jun. 2022, doi: 10.1007/s00330-021-08504-6.
- [8] V. S. Parekh *et al.*, "Multiparametric deep learning tissue signatures for a radiological biomarker of breast cancer: preliminary results," *Medical Physics*, vol. 47, no. 1, pp. 75–88, Jan. 2020, doi: 10.1002/mp.13849.
- [9] R. Lo Gullo, S. Eskreis-Winkler, E. A. Morris, and K. Pinker, "Machine learning with multiparametric magnetic resonance imaging of the breast for early prediction of response to neoadjuvant chemotherapy," *The Breast*, vol. 49, pp. 115–122, Feb. 2020, doi: 10.1016/j.breast.2019.11.009.
- [10] N. F. Aurna, M. A. Yousuf, K. A. Taher, A. K. M. Azad, and M. A. Moni, "A classification of MRI brain tumor based on two stage feature level ensemble of deep CNN models," *Computers in Biology and Medicine*, vol. 146, p. 105539, Jul. 2022, doi: 10.1016/j.combiomed.2022.105539.
- [11] H. Saleh, S. F. Abd-el ghany, H. Alyami, and W. Alosaimi, "Predicting breast cancer based on optimized deep learning approach," *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–11, Mar. 2022, doi: 10.1155/2022/1820777.
- [12] D. Muduli, R. Dash, and B. Majhi, "Automated diagnosis of breast cancer using multi-modal datasets: A deep convolution neural network based approach," *Biomedical Signal Processing and Control*, vol. 71, p. 102825, Jan. 2022, doi: 10.1016/j.bspc.2021.102825.
- [13] N. Chouhan, A. Khan, J. Z. Shah, M. Hussnain, and M. W. Khan, "Deep convolutional neural network and emotional learning based breast cancer detection using digital mammography," *Computers in Biology and Medicine*, vol. 132, p. 104318, May 2021, doi: 10.1016/j.combiomed.2021.104318.
- [14] A. M. Alqudah, S. Qazan, and I. S. Masad, "Artificial intelligence framework for efficient detection and classification of pneumonia using chest radiography images," *Journal of Medical and Biological Engineering*, vol. 41, pp. 599–609, Jun. 2021, doi: 10.1007/s40846-021-00631-1.
- [15] S. Nadkarni and K. Noronha, "Breast cancer detection using ensemble of convolutional neural networks," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 14, no. 1, pp. 1041–1047, Feb. 2024, doi: 10.11591/ijece.v14i1.pp1041-1047.
- [16] T. Shah and S. Guraya, "Breast cancer screening programs: Review of merits, demerits, and recent recommendations practiced across the world," *Journal of Microscopy and Ultrastructure*, vol. 5, no. 2, pp. 59–69, 2017, doi: 10.1016/j.jmau.2016.10.002.
- [17] J. Hall, "Mammography and breast MRI: is it time to evaluate strategies as opposed to modalities?," *Journal of the American College of Radiology*, 2024.
- [18] D. Leithner *et al.*, "Clinical role of breast MRI now and going forward," *Clinical Radiology*, vol. 73, no. 8, pp. 700–714, Aug. 2018, doi: 10.1016/j.crad.2017.10.021.
- [19] S. Nadkarni and K. Noronha, "A review on multiparametric magnetic resonance imaging for the detection of breast cancer," in *2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT)*, IEEE, Jul. 2020, pp. 1–5, doi: 10.1109/CONECCT50063.2020.9198362.
- [20] Q. Hu, H. M. Whitney, and M. L. Giger, "A deep learning methodology for improved breast cancer diagnosis using multiparametric MRI," *Scientific Reports*, vol. 10, no. 1, p. 10536, Jun. 2020, doi: 10.1038/s41598-020-67441-4.
- [21] M. A. Hossain and M. S. Alam Sajib, "Classification of image using convolutional neural network (CNN)," *Global Journal of Computer Science and Technology*, pp. 13–18, 2019, doi: 10.34257/gjcstdvol19is2pg13.
- [22] M. A. Al-masni *et al.*, "Simultaneous detection and classification of breast masses in digital mammograms via a deep learning YOLO-based CAD system," *Computer Methods and Programs in Biomedicine*, vol. 157, pp. 85–94, Apr. 2018, doi: 10.1016/j.cmpb.2018.01.017.
- [23] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, May 2017, doi: 10.1145/3065386.
- [24] L. Sun *et al.*, "Cross-attention multi-branch CNN using DCE-MRI to classify breast cancer molecular subtypes," *Frontiers in Oncology*, vol. 13, Mar. 2023, doi: 10.3389/fonc.2023.1107850.
- [25] K. A. Abdullah, S. Marzali, M. Nanaa, L. Escudero Sánchez, N. R. Payne, and F. J. Gilbert, "Deep learning-based breast cancer diagnosis in breast MRI: systematic review and meta-analysis," *European Radiology*, vol. 35, no. 8, pp. 4474–4489, Feb. 2025, doi: 10.1007/s00330-025-11406-6.
- [26] H. Zheng, L. Jian, L. Li, W. Liu, and W. Chen, "Prior clinico-radiological features informed multi-modal MR images convolution neural network: a novel deep learning framework for prediction of lymphovascular invasion in breast cancer," *Cancer Medicine*, vol. 13, no. 3, Feb. 2024, doi: 10.1002/cam4.6932.
- [27] A. Ashfaq, Y. Wenhui, S. Jinhai, and M. U. Nasir, "Breast cancer diagnosing empowered with transfer learning," in *2022 IEEE 8th International Conference on Computer and Communications (ICCC)*, IEEE, Dec. 2022, pp. 2292–2297, doi: 10.1109/ICCC56324.2022.10065787.

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