GLCM and CNN Deep Learning Model for Improved MRI Breast Tumors Detection

https://doi.org/10.3991/ijoe.v18i12.31897

Aya A. Alsalihi[1(✉)], Hadeel K. Aljobouri[2(✉)], Enam Azez Khalel ALTameemi[3]
[1]Control and Inspection Department, Diyala Directorate of Health, Iraqi Ministry of Health, Diyala, Iraq
[2]Biomedical Engineering Department, College of Engineering, Al-Nahrain University, Baghdad, Iraq
[3]Radiology Department, Oncology Teaching Hospital, Baghdad Medical City, Baghdad, Iraq
ayaalsalihi707@gmail.com
hadeel_bme77@yahoo.com

Abstract—Breast cancer is one of the most common types of cancer among Iraqi women. MRI has been used in the detection of breast tumors for its efficient performance in the diagnosis process providing high accuracy. In this paper, breast MRI image data from 89 patients were classified using GLCM and CNN feature extraction methods. Four models were evaluated consisting of GLCM, CNN, combined GLCM and CNN features based models. The statistical ANOVA feature selection method was used to reduce the redundant features. The reduced feature subset was fed to CNN classifier for obtaining either normal or abnormal breast images. The proposed method was assessed in terms of accuracy, precision, recall and F1-score. The model provided 100% classification accuracy.

Keywords—ANOVA, breast cancer MRI, CNN, feature extraction, GLCM

1 Introduction

Breast cancer is the most presenting type of cancer in women. It develops in breast tissue [1]. In Iraq, it is the most common cancer type ranking first among other cancer types in women [2], particularly, in the period 2012–2019 in Al-Hussein cancer center in Kerbala province in Iraq [3].

Magnetic Resonance Imaging (MRI) is one of the major medical imaging techniques that play important role in achieving an accurate diagnosis of cancer including breast cancer [4][5] for its high accuracy, specificity, and sensitivity even in dense breast tissue [6]. MRI enables radiologists to better recognize benign and malignant lesions [7][8][9]. Adding MRI to Mammography when screening for breast cancer has elevated cancer detection [10].

One of the branches in computer science involved with creating models inspired by human intelligence is Artificial Intelligence (AI), these models perform tasks usually performed by humans. AI Figure 1 has been used to enhance the performance of MRI in cancer detection and recognition of the cancer type [7]. When certain algorithms within AI models are trained to recognize certain patterns or features within the data, then these algorithms are considered Machine Learning algorithms (ML). Machine learning algorithms have successfully assisted in the diagnosis of several diseases when integrated into medical imaging [11][12]. Deep learning (DL) is a subtype algorithm of ML, in which the algorithm learns to recognize a group of features and thus identify the components in an image [13].

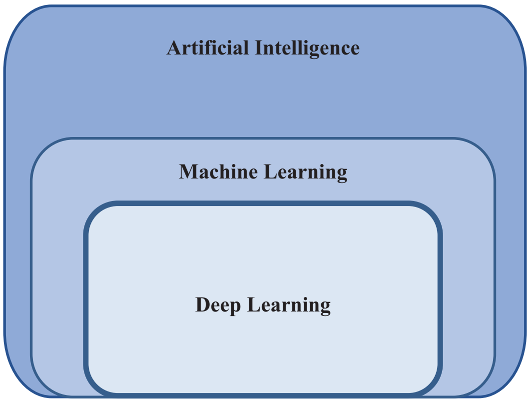


Fig. 1. Diagram showing AI, ML, and DL with respect to each other

Many related works were performed in this area. In 2008, Wang et al. compared support vector machine (SVM) to C-Means in the classification of multi spectral MR images of the breast [14]. In 2012, Hassanain & Kim presented a Hybrid approach to classify breast MR images for presenting cancer. In a preprocessing step a type-II fuzzy set was used in conjunction with pulse coupled neural networks (PCNN) to prepare the images for feature extraction. Wavelet transform feature extraction was employed to extract the features which were normalized. SVM was finally used for the purpose of classification [15]. In 2012, Kumar Mohanty et al. proposed a model for classifying benign and malignant lesions in mammography images. The images were first preprocessed by the application of low pass filter to reduce noise. Region of Interest (ROI) was next identified. 19 Gray Level Co-occurrence Matrix (GLCM) and Gray Level Run Length Matrix (GLRLM) were extracted. This was followed by classification using Association Rule Mining method [16]. In 2013, Nagarajan et al., investigated the effect of post contrast extracted features on classification performance. MRI images of 54 female patients were used in the model. After preprocessing, GLCM features were extracted in four directions. Harlick features were extracted using non-directional GLCM. Feature subset was obtained using Mutual Information feature selection. These features were then classified using fuzzy K Nearest Neighbor (fKNN), Support Vector Regression algorithm with radial basis function kernel (RBF-SVR) and linear function kernel (SVRlin) [17]. In 2019, Zhang et al., proposed a Mask Guided Hierarchical Learning (MHL) for the purpose of breast tumor segmentation. Fully Convolutional Network (FCN) was first trained to detect ROI named (FCN-1). Then FCN-2 was made for rough estimation of segmentation results. Initial results were refined by FCN-3. And an FCN-4 model was used to detect two landmarks at the nipples. The model was finally validated on 272 cases [18]. However, in 2019, Alkhaleefah & Wu implemented transfer learning model on breast mammography images. Since few numbers of images were available, Convolution Neural Network (CNN) was established from zero and trained on MRI spine images. The parameters learned from CNN were fed to Radial Basis Function SVM (RBF-SVM) for classification [19]. In 2020, Yurttakal et al. implemented a model on 200 tumor images to detect breast cancer. Data was preprocessed and denoised by using Denoising Deep Neural Network (DnCNN). This was followed by data augmentation to avoid overfitting. A CNN model was then employed for classification [20]. In 2021, Jaglan et al. utilized the breast MR images of 448 patients. The data was preprocessed aiming to remove gaussian noise using Median filter and Weiner filter. This was followed by segmentation of breast region and detection of tumor. Features of shape, size, texture, and contrast were extracted. There were 27 features eventually classified by SVM [21]. Furthermore, in 2021, Hilal et al. proposed a model to classify MRI breast scans. 326 images were first preprocessed using gaussian filter, symmetry detection, and intensity normalization. GLCM and GLRLM were used to extract features which have been reduced using ANOVA feature selection. Long Short-Term Memory (LSTM) was used for the classification of breast MR images into normal or abnormal [22]. Due to the lack of cancer centers in Iraq, and for the bare reason of lack of histopathological confirmed MRI scans, free data was employed to conduct this study. In this proposed model, a breast cancer classification problem was addressed using GLCM and CNN feature extraction. Feature vectors were extracted from T2W breast MRI images. Features spaces were reduced using ANOVA. Finally, features were classified using dense layers into normal and abnormal breast scan.

2 Methodology

This study aims to implement GLCM, and CNN features based model that helps radiologists in the loaded clinical settings in Iraq to efficiently diagnose the normal and abnormal breast scans using CNN dense layers. Consequently, the classification model can be employed for better management of pathological cases by reducing the time consumed by normal scans, through automatic classification of the image type fed to the model. This will provide an initial diagnosis to the radiologist and will help to speed the process up when normal scan is identified. Thus, more time can be dedicated to scans that are being classified as abnormal. There is very limited use of AI models in Iraqi clinics and cancer centers due to limited resources. Adding AI models is more efficient and time saving compared to radiologist's own speed in processing the scan and classifying the type of the image. Figure 2 is a small diagram representation of the proposed model.

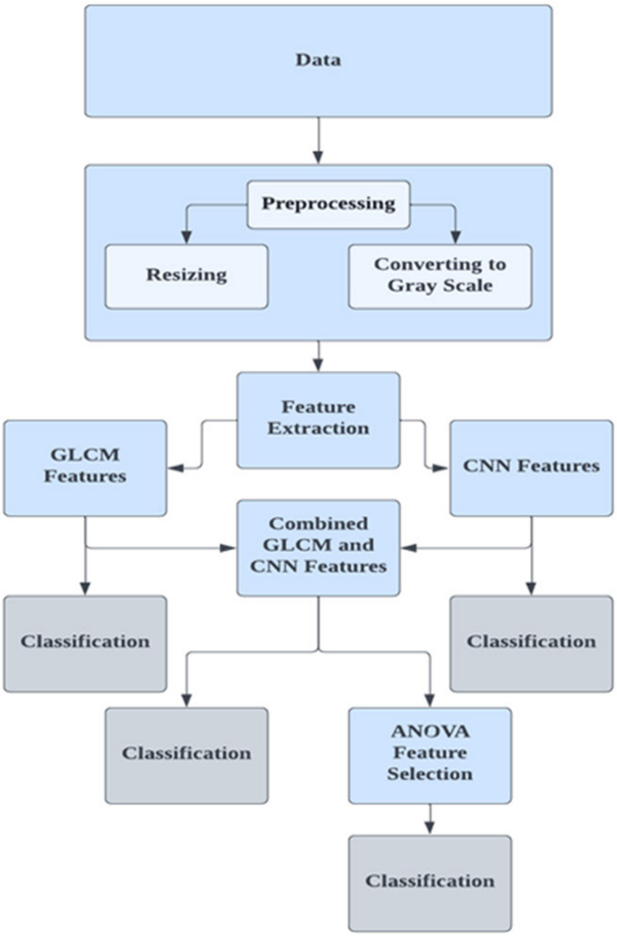


Fig. 2. Diagram representation of the proposed model

2.1 Data

MRI breast image data from BREAST-DIAGNOSIS. The Cancer Imaging Archive. http://doi.org/10.7937/K9/TCIA.2015.SDNRQXXR was used in this study and obtained from the Cancer Image Archive (TCIA) [23]. The data set includes images from 89 patients, normal and abnormal breast images were obtained from STIR and T2W modalities. In addition to the ground truth table of the free data supplied by TCIA, a second ground truth table for the data was established by three experienced Iraqi radiologists for the total 326 MRI breast images. 1.5 Tesla PHILIPS Achieva scanner was used to obtain the MRI breast scan. This data collection contains a range of cases extending from normal cases such as high risk normal and abnormal scans such as fibroid, lobular, and Ductal Carcinoma in Situ. Some patients have been investigated on multiple time points. The data is supplemented with BIRADS MRI features provided by the imaging report. If a mass was found, X-Y center position of the mass is provided in key images. In this study, 161 abnormal and 165 normal MRI images from T2W modality were investigated, Figure 3 below includes sample images used in this study.

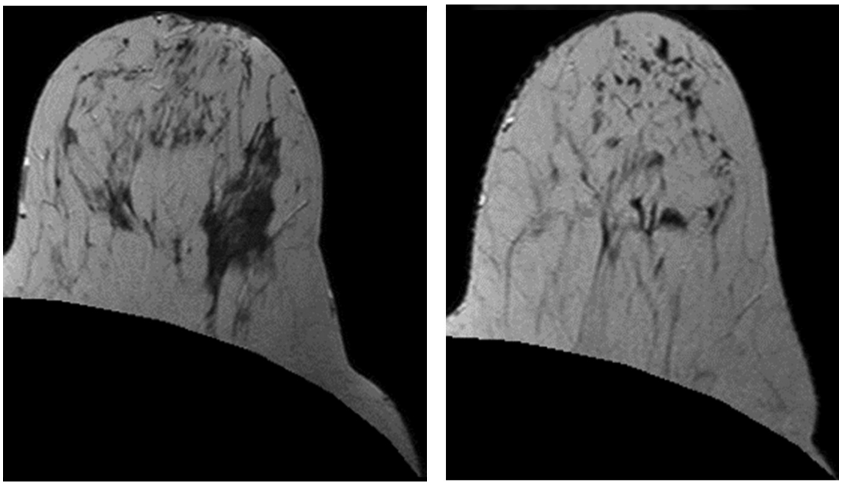


Fig. 3. Sample T2W breast MRI image used in this study

2.2 Preprocessing

The images were preprocessed for preparation of feature extraction step. The images were resized to a uniform new size for all the data. All the images were converted from RGB into grayscale to construct basis for providing statistical information about the gray levels between adjacent pixels. This step will help to extract Gray Level Co-occurrence Matrix features.

3 Feature extraction

In order to obtain a model with reliable and efficient performance, feature extraction was handled with more attention. In this study two types of feature extractors were employed in the proposed model for the problem of breast cancer classification. The first feature set is GLCM which was used to extract Harlick texture features from the images. GLCM was first introduced in 1973 by Robert Harlick [24]. GLCM is used to extract texture features by measuring the spatial relationship between reference and neighbor pixels. Two variables are considered while assessing GLCM features. The distance (d) between the two pixels of concern and the direction (θ) in which the pixel relations are assessed [25].

The second is the high-level features, those were extracted using CNN algorithm. CNN was first introduced in 1980s [26]. CNN is a deep learning algorithm that is characterized by its ability to extract the most important features for classification independent of the spatial occurrence in the images. The Convolution layer plays important role in CNN [27]. In this paper, CNN features were extracted by the convolution layer. In both cases features were normalized, scaled to unit variance by removing mean.

Normalization is important for improving the model accuracy by assuring smooth transition towards the minima in the optimization phase.

3.1 GLCM features

52 Harlick texture features were extracted from the images using GLCM. 14 features were obtained from 4 matrices of GLCM. The 4 matrices were calculated using 4 distance separations between reference pixel and the neighbor pixel. The GLCM was also calculated in four different angles (0°, 45°, 90°, and 135°). With the purpose of reducing computation time only 13 features were considered in this study. Thus total 52 features were extracted consisting of 13 Harlick features from each one of the 4 GLCM matrices. Below are the 14 Harlick features names:

- Angular Second Moment (homogeneity).
- Contrast.
- Correlation.
- Sum of Squares (Variance).
- Inverse Difference Moment (local homogeneity).
- Sum Average.
- Sum Variance.
- Sum Entropy.
- Entropy.
- Difference Variance.
- Difference Entropy.
- Information Measures of Correlation 1.
- Information Measure of Correlation 2.
- Maximal Correlation Coefficient: was not calculated to reduce computation complexity.

3.2 CNN features

CNN was utilized to extract features from the breast MRI images, three layers of convolution were built, and these layers extracted high level features form the labeled images in the training portion in the input data. 4 kernels of the size (3×3) were used in the convolutional layer. This was followed by MaxPooling layer of the size (2×2). The stride was also 2. These two layers were repeated with only different number of kernels. 8 kernels were used in the next block and 20 on the third block. The Relu activation function was used in all the convolutional layers. A flattening layer was finally used to hold the features in a one-dimensional matrix.

4 Feature selection

A statistical feature selection method was used to reduce the feature space, eliminating the non-relevant features, and dedicating more priority to important features. Selecting the most important features can significantly improve model performance [28]. Analysis of variance (ANOVA) is feature selection algorithm categorized within filter methods of feature selection. F score is one statistical way in which ratio of variance is measured among variables within and between groups [29]. ANOVA has been utilized by many researchers to reduce the feature spaces and eliminate non relevant features [30][31][32][33]. In this study ANOVA feature selection method was used to reduce the feature dimensions of the combined GLCM and CNN feature sets. F- Statistics for each feature was calculated by employing ANOVA. This helps to identify features with good discrimination capabilities between the two classes.

5 Classification

Four models were used in this study for the purpose of classifying breast MRI images into normal and abnormal. In the first model the GLCM Harlick features were classified using 5 dense layers, drop out was used between the dense layers to reduce overfitting. In this study we have two classes in the problem of classification into normal and abnormal breast MRI images. For this reason, a sigmoid activation function was employed.

The second model consisted of high-level feature extracted using CNN were classified using 3 dense layers with sigmoid as an activation function.

In the third model, the texture features from GLCM and high-level features from CNN were integrated with each other and the features from this combination were then classified by dense layer.

In the fourth model, the combined GLCM and CNN features were reduced into a feature subset selected by ANOVA. The reduced set of features were classified using dense layer. Figure 4 shows a representation of the proposed model architecture.

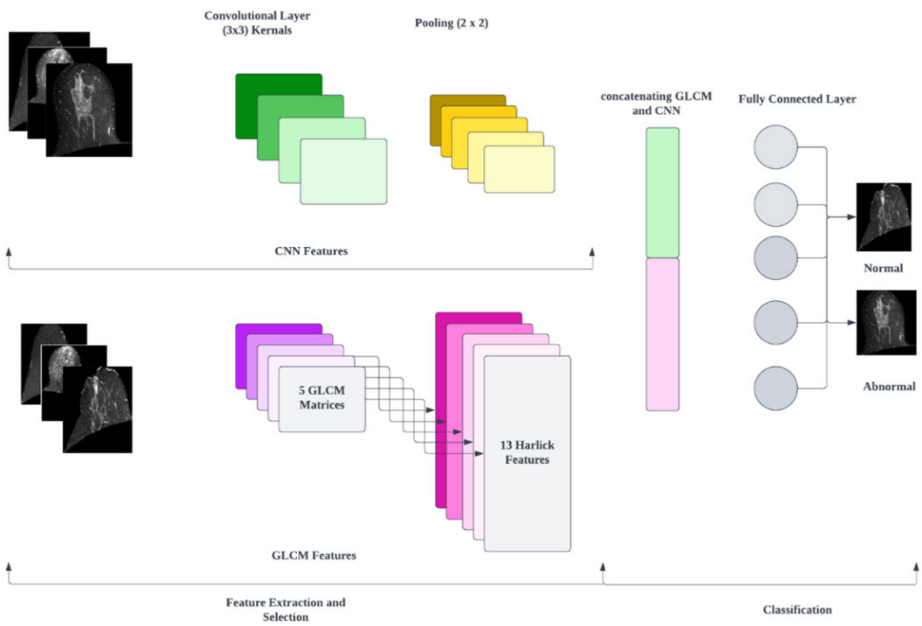


Fig. 4. Representation of the proposed model architecture

6 Results

This study has presented a proposal for classifying 326 breast normal and abnormal MRI images using GLCM and CNN features. The two methods for feature extraction were used individually and in combination with each other during the development of the model. Model accuracy, precision, recall, and F1-s score (sensitivity) were measured for the four models through the employment of the confusion matrix. Figure 5 depicts confusion matrices obtained during the development of four models in this study, where the x-axis represent the predicted labels while the y-axis represents the actual labels. True Negative (TN), True positive (TP), False Negative (FN), False Positive (FP) values have been employed through the following formulas:

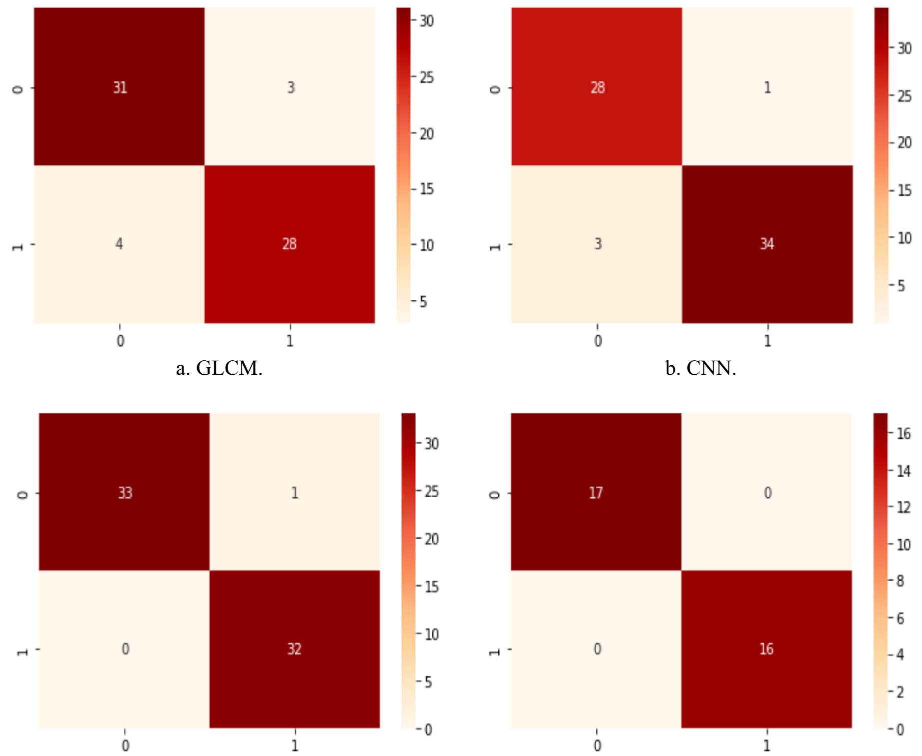
$$Accuracy = (TP + TN)/(TP + FP + FN + TN) \times 100\% \quad (1)$$

$$Precision = TP/(TP + FP) \times 100\% \quad (2)$$

$$Recall = TP/(TP + FN) \times 100\% \quad (3)$$

$$F1\ score = (2 \times (Recall \times Precision)/(Recall + Precision)) \times 100\% \quad (4)$$

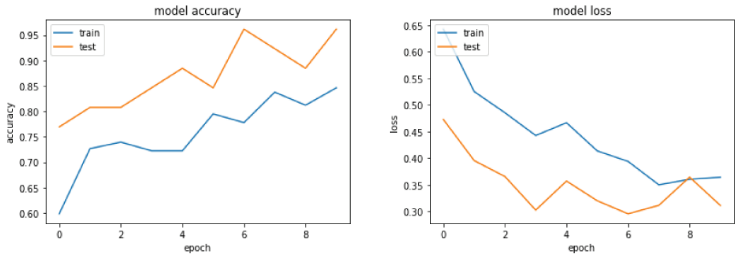
Loss and accuracy curves have been plotted for each model. Figure 6 depicts plots of model accuracy in which the x-axis represents the number of epochs while the y-axis represent the model accuracy over the corresponding epoch, and model loss plots where the x-axis represent the number of epochs and the y-axis represent the model loss over the corresponding epoch. The plots represent the model performance for 10 epochs during training and testing phases. The data was divided into 80% for training and 20% testing.



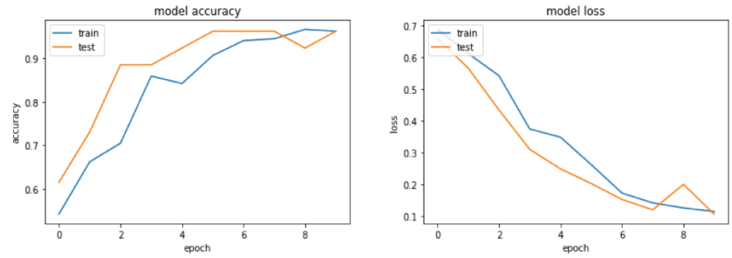
a. GLCM. b. CNN.

c. CNN + GLCM. d. ANOVA.

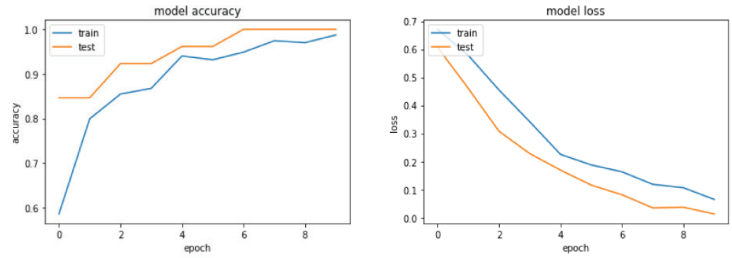
Fig. 5. Confusion matrix of the True Negative (TN), True Positive (TP), False Negative (FN), False Positive (FP) values, for (a) GLCM features model, (b) CNN features model, (c) combined GLCM and CNN features model, (d) the model based on ANOVA feature selection of the GLCM and CNN combined features



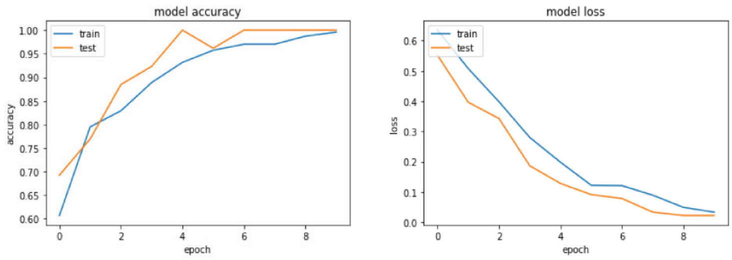
a. GLCM.



b. CNN.



c. CNN + GLCM.



d. ANOVA.

Fig. 6. Represent plots of model accuracy, and model loss plots. The plots represent the model performance for 10 epochs during training and testing phases. (a) reflect the performance of model which relies on the GLCM features alone. (b) the performance of the model depending on CNN features. (c) combined GLCM and CNN features model performance. (d) model performance with the reduced features subset by ANOVA

The GLCM based model has achieved the lowest accuracy of (89.3%). It is believed this result was obtained due to dependance on one type features which was Harlick texture features, meaning, for the classification model in hand, there is room for improving the model performance by adding other features to GLCM. CNN was (93.9%) accurate, this reflects the fact that CNN is capable of learning the important features. CNN assigns more weights to the features which show valuable addition to the model performance, this made the CNN perform better than the GLCM feature based method. The model which was based on combined GLCM+CNN features attained an accuracy of (98.4%). The improvement in the combined GLCM and CNN model regarding accuracy is believed to be due to the addition of the Harlick texture features extracted through GLCM to the CNN features. This made the model familiar with both texture and high-level features. This refers to the fact that GLCM based model performance has improved in terms of accuracy after adding features from CNN. So is the case about CNN accuracy, both models improved after combining the features. The last model has achieved an accuracy of (100%) given that the ANOVA feature selection has eliminated all the unnecessary features that may negatively affect the performance of the model in terms of accuracy and time. the Table 1 below shows a detailed performance of each model in terms of Precision, Recall, F1-score, and Accuracy.

Table 1. Performance of the proposed models

Model	TP	TN	FP	FN	Precision	Recall	F1-score	Accuracy
GLCM	28	31	3	4	90.3%	87.5%	88.8%	89.3%
CNN	34	28	1	3	97.1%	91.8%	94.4%	93.9%
GLCM & CNN	32	33	1	0	96.9%	100%	98.4%	98.4%
GLCM & CNN/ANOVA	16	17	0	0	100%	100%	100%	100%

7 Discussion

This research proposed a method to solve a classification problem of the breast MRI images consisting for data set of 161 abnormal and 167 normal breast images obtained from T2W MRI modality. GLCM features were used to detect important texture features in the images in preparation for classification. GLCM model was found to be lacking the superior accuracy on its own. However, the classification that is solely dependent on GLCM features can achieve fair performance, especially when being integrated with the suitable classifier.

Features such as wavelet transform [15], pre trained CNN features [19], and high-level CNN features which have been assessed in this study may provide more accepted classification accuracy. Shape, size, texture, and contrast features could also perform well when using efficient classifiers [21]. Combining GLCM features with other feature extraction methods can drastically increase model performance. Adding GLRLM features to GLCM before classification step gave good results and elevated GLCM performance resulting in (94.9%) classification accuracy [16].

Good performance (95% accuracy) was achieved on the data processed in this research in 2018 by Detheridge et al. when using CNN algorithm for both feature extraction and classification [34]. Reducing GLCM and GLRLM combination feature space by using ANOVA feature selection method for the same data from TCIA provided excellent results (98.8%) after classification by using LSTM classifier [22].

In this paper, GLCM features performance was explored on classification, which provided an accuracy of (89.3%). CNN features were also explored in terms of classification accuracy showing to be (93.9%) accurate. Also, GLCM was used in combination with CNN features, and it proved to provide superior results (98.4%) when compared to other combinations. Classification model performance was further improved when applying feature selection method.

In our proposed method, ANOVA was used to reduce features combination obtained from GLCM and CNN. Classifying the reduced subset by CNN provided higher accuracy (100%) than the previous models. Table 2 below shows analysis of some previous methods introduced for solving similar classification problems in comparison with the model proposed in this paper.

Table 2. Analysis for the purpose of comparing to previous methods

Features	Classification	Data	Author	Model Accuracy
Wavelet transform	SVM	MR breast images	2018, Hassanain & Kim [15]	98%
Pre-trained CNN	RBF-SVM classification	breast mammography images	2019, Alkhaleefah & Wu [19]	92%
Shape, size, texture, and contrast	SVM	Breast MR images	2021, Jaglan et al. [21]	93%
GLCM, GLRLM	Association Rule Mining classification	Mammography breast images	2012, Kumar Mohanty et al. [16]	94.9%
CNN	CNN	TCIA MR breast images	2012, Detheridge et al. [34]	95%
GLCM, GLRLM, ANOVA (feature selection)	LSTM	TCIA breast MR images	2021, Hilal et al. [22]	98.80%
GLCM, CNN, combined GLCM and CNN, ANOVA	CNN	TCIA breast MR images	Proposed method	100%

8 Conclusion

Depending on the considerations in this study, we can come to an end that GLCM texture features can provide a solution for classification of breast MR images, although feature extractors such as CNN can have better performance. However, GLCM alone is not ideal when high accuracy is the goal for clinical applications. Adding other feature extractors to GLCM, such as CNN proved to be successful in elevating the outcome. Further leverage can be achieved when employing a statistical feature selection method such as ANOVA before classification. This model is a possible solution for the loaded clinical context in Iraq. Since there is a recognized shortage in terms of clinical investigation and diagnosis possibilities, this model was built with the intention of providing means to aid radiologist in the diagnosis process and increase number of patients receiving clinical care by reducing time consumed by normal breast scans.

9 References

[1] G. N. Sharma, R. Dave, J. Sanadya, P. Sharma, and K. K. Sharma, "Various types and management of breast cancer: An overview," *J. Adv. Pharm. Tech. Res*, vol. 1, no. 2, [Online]. Available: https://www.japtr.org

[2] N. A. S. Alwan, F. N. Tawfeeq, and N. A. G. Mallah, "Demographic and clinical profiles of female patients diagnosed with breast cancer in Iraq," *Journal of Contemporary Medical Sciences*, vol. 5, no. 1, pp. 14–19, Feb. 2019, https://doi.org/10.22317/jcms.v5i1.544

[3] Ahmed Mjali and Bushra Najeh Hasan Al Baroodi, "Some facts about cancer in Karbala province of Iraq, 2012–2020," 2020, https://doi.org/10.31557/apjcc.2020.5.2.67-69

[4] Steven E. Harms, "MRI in breast cancer diagnosis and treatment," *Current Problems in Diagnostic Radiology*, vol. 25, no. 6, pp. 192–215, 1996, https://doi.org/10.1016/S0363-0188(96)90009-2

[5] 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, Dec. 2020, https://doi.org/10.1038/s41598-020-67441-4

[6] M. Morrow, J. Waters, and E. Morris, "MRI for breast cancer screening, diagnosis, and treatment," *The Lancet*, vol. 378, no. 9805. Elsevier B.V., pp. 1804–1811, 2011, https://doi.org/10.1016/S0140-6736(11)61350-0

[7] Y. Jiang, A. v. Edwards, and G. M. Newstead, "Artificial intelligence applied to breast MRI for improved diagnosis," *Radiology*, vol. 298, no. 1, pp. 38–46, 2021, https://doi.org/10.1148/radiol.2020200292

[8] M. de Rooij, E. H. J. Hamoen, J. J. Fütterer, J. O. Barentsz, and M. M. Rovers, "Accuracy of multiparametric MRI for prostate cancer detection: A meta-analysis," *American Journal of Roentgenology*, vol. 202, no. 2, pp. 343–351, Feb. 2014, https://doi.org/10.2214/AJR.13.11046

[9] V. R. Iyer and S. I. Lee, "MRI, CT, and PET/CT for ovarian cancer detection and adnexal lesion characterization," *American Journal of Roentgenology*, vol. 194, no. 2. pp. 311–321, Feb. 2010, https://doi.org/10.2214/AJR.09.3522

[10] W. A. Berg et al., "Detection of breast cancer with addition of annual screening ultrasound or a single screening MRI to mammography in women with elevated breast cancer risk," *JAMA – Journal of the American Medical Association*, vol. 307, no. 13, pp. 1394–1404, 2012, https://doi.org/10.1001/jama.2012.388

[11] N. N. Khamiss, "Unsupervised segmentation method for brain MRI based on fuzzy techniques," *Nahrain University, College of Engineering Journal*, vol. 13, no. 1, pp. 108–115, 2010.

[12] T. A. U.-M. Sadoon and M. H. Ali, "Coronavirus 2019 (COVID-19) detection based on deep learning" *Al-Nahrain Journal for Engineering Sciences*, vol. 23, no. 4, pp. 408–415, Dec. 2020, https://doi.org/10.29194/NJES.23040408

[13] G. Chartrand et al., "Deep learning: A primer for radiologists," *Radiographics*, vol. 37, no. 7. Radiological Society of North America Inc., pp. 2113–2131, Nov. 01, 2017. https://doi.org/10.1148/rg.2017170077

[14] C. M. Wang, X. X. Mai, G. C. Lin, and C. T. Kuo, "Classification for breast MRI using support vector machine," in *Proceedings - 8th IEEE International Conference on Computer and Information Technology Workshops, CIT Workshops 2008*, 2008, pp. 362–367, https://doi.org/10.1109/CIT.2008.Workshops.90
[15] A. E. Hassanien and T. H. Kim, "Breast cancer MRI diagnosis approach using support vector machine and pulse coupled neural networks," in *Journal of Applied Logic*, 2012, vol. 10, no. 4, pp. 277–284, https://doi.org/10.1016/j.jal.2012.07.003
[16] A. K. Mohanty, S. Beberta, and S. K. Lenka, "Classifying benign and malignant mass using GLCM and GLRLM based texture features from Mammogram," *International Journal of Engineering Research and Applications (IJERA)*, vol. 1, no. 3, pp. 687–693, 2011, [Online]. Available: https://www.ijera.com
[17] M. B. Nagarajan, M. B. Huber, T. Schlossbauer, G. Leinsinger, A. Krol, and A. Wismüller, "Classification of small lesions in breast MRI: Evaluating the role of dynamically extracted texture features through feature selection," *Journal of Medical and Biological Engineering*, vol. 33, no. 1, pp. 59–68, 2013, https://doi.org/10.5405/jmbe.1183
[18] J. Zhang, A. Saha, Z. Zhu, and M. A. Mazurowski, "Hierarchical convolutional neural networks for segmentation of breast tumors in MRI with application to radiogenomics," *IEEE Transactions on Medical Imaging*, vol. 38, no. 2, pp. 435–447, Feb. 2019, https://doi.org/10.1109/TMI.2018.2865671
[19] M. Alkhaleefah and C. C. Wu, "A hybrid CNN and RBF-based SVM approach for breast cancer classification in Mammograms," in *Proceedings – 2018 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2018*, Jan. 2019, pp. 894–899, https://doi.org/10.1109/SMC.2018.00159
[20] A. H. Yurttakal, H. Erbay, T. İkizceli, and S. Karaçavuş, "Detection of breast cancer via deep convolution neural networks using MRI images," *Multimedia Tools and Applications*, vol. 79, no. 21–22, pp. 15555–15573, Jun. 2020, https://doi.org/10.1007/s11042-019-7479-6
[21] P. Jaglan, R. Dass, and M. Duhan, "An automatic and efficient technique for tumor location identification and classification through breast MR images," *Expert Systems with Applications*, vol. 185, Dec. 2021, https://doi.org/10.1016/j.eswa.2021.115580
[22] S. R. Hilal, H. S. Hasan, and A. M. Hasan, "Magnetic resonance imaging breast scan classification based on texture features and long short-term memory model," *NeuroQuantology*, vol. 19, no. 7, pp. 41–47, 2021, https://doi.org/10.14704/nq.2021.19.7.NQ21082
[23] K. Clark et al., "The cancer imaging archive (TCIA): Maintaining and operating a public information repository," *Journal of Digital Imaging*, vol. 26, no. 6, pp. 1045–1057, Dec. 2013, https://doi.org/10.1007/s10278-013-9622-7
[24] M. A. Shafiq, Z. Wang, A. Amin, T. Hegazy, M. Deriche, and G. AlRegib, "Detection of salt-dome boundary surfaces in migrated seismic volumes using gradient of textures," in *SEG Technical Program Expanded Abstracts*, 2015, vol. 34, pp. 1811–1815, https://doi.org/10.1190/segam2015-5927230.1
[25] A. Ramola, A. K. Shakya, and D. van Pham, "Study of statistical methods for texture analysis and their modern evolutions," *Engineering Reports*, vol. 2, no. 4, Apr. 2020, https://doi.org/10.1002/eng2.12149
[26] K. Fukushima, "Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position," *Biological Cybernetics*, vol. 36, no. 4, pp. 193–202, 1980, https://doi.org/10.1007/BF00344251
[27] S. Albawi, T. A. M. Mohammed, and S. Alzawi, "Layers of a Convolutional Neural Network," *Ieee*, p. 16, 2017, https://doi.org/10.1109/ICEngTechnol.2017.8308186
[28] F. Zahedi and M. K. Moridani, "Classification of breast cancer tumors using mammography images processing based on machine learning," vol. 18, no. 05, pp. 31–42, 2022, https://doi.org/10.3991/ijoe.v18i05.29197

[29] R. Dhanya, I. R. Paul, S. S. Akula, M. Sivakumar, and J. J. Nair, "F-test feature selection in Stacking ensemble model for breast cancer prediction," in *Procedia Computer Science*, 2020, vol. 171, pp. 1561–1570, https://doi.org/10.1016/j.procs.2020.04.167
[30] H. Yu et al., "Predicting the level of tumor-infiltrating lymphocytes in patients with breast cancer: Usefulness of mammographic radiomics features," *Frontiers in Oncology*, vol. 11, Mar. 2021, https://doi.org/10.3389/fonc.2021.628577
[31] Z. Wang et al., "Contrast-enhanced spectral mammography-based radiomics nomogram for the prediction of neoadjuvant chemotherapy-insensitive breast cancers," *Frontiers in Oncology*, vol. 11, Feb. 2021, https://doi.org/10.3389/fonc.2021.605230
[32] B. M. Gayathri and C. P. Sumathi, "Comparative study of relevance vector machine with various machine learning techniques used for detecting breast cancer," 2017, https://doi.org/10.1109/ICCIC.2016.7919576
[33] S. K. Wajid and A. Hussain, "Local energy-based shape histogram feature extraction technique for breast cancer diagnosis," *Expert Systems with Applications*, vol. 42, no. 20, pp. 6990–6999, Jun. 2015, https://doi.org/10.1016/j.eswa.2015.04.057
[34] P. Saponara, C. Detheridge, J. Bhangu, B. N. Bloch, and K. Thomas, "Diagnostic Assessment of Intracranial Tumor Types Through an Artificial Intelligence Machine Learning Algorithm," 2018.

10 Authors

Aya A. Alsalihi obtained B.S. in Biomedical Engineering from Al-Nahrain in 2015, currently studying M.Sc. in Biomedical Engineering. Worked as a bio-medical Engineer in the Diyala Directorate of Health. Interested in the applications of Artificial Intelligence in the medical field (email: ayaalsalihi707@gmail.com; https://orcid.org/0000-0002-3507-657X).

Hadeel K. Aljobouri received the B.S. degree in Biomedical Engineering from the University of Baghdad, Baghdad, Iraq, in 2000 the M.Sc. in Medical Engineering from Al-Nahrain University, Baghdad, Iraq, in 2004, and the Ph.D. at the Electrical and Electronics Engineering Department, Graduate School of Natural Science/ Ankara Yildirim Beyazit University in Turkey. She worked as an Assistant Professor at the Biomedical Engineering Department at Al-Nahrain University in Iraq. Her research interests are biomedical signal processing, medical imaging, data mining, clustering techniques, and machine learning. She has many publications in the field of biomedical engineering (email: hadeel_bme77@yahoo.com; https://orcid.org/0000-0003-1792-9230).

Enam Azez Khalel ALTameemi, Radiology Department, Oncology Teaching Hospital, Baghdad Medical City, Baghdad, Iraq.

Article submitted 2022-05-08. Resubmitted 2022-06-14. Final acceptance 2022-06-21. Final version published as submitted by the authors.