Received: April 28, 2022. Revised: May 18 2022.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Exploiting the Performance of Marine Predators Optimization Algorithm in Combination with Neural Network Classifiers for Breast Mass Classification

Harmandeep Singh[1]* **Vipul Sharma**[1] **Damanpreet Singh**[2]

[1]*Department of Computer Science and Engineering, IKG Punjab Technical University, Jalandhar, 144603, India*
[2]*Department of Computer Science and Engineering, Sant Longowal Institute of Engineering and Technology, Sangrur, 148106, India*
* Corresponding author's Email: singh.harman.saini@gmail.com

Abstract: Recently, breast cancer has achieved top position in terms of cause of mortality among women of all age groups by surpassing the lung cancer. To improve the survival rate, timely assessments are essential. Mammography is the best modality among the most widely used timely detection modalities. The radiologists' manual reading may have an impact on the accuracy of the diagnosis. As a result, the computer-aided diagnosis (CAD) systems are being developed as tools to reduce the false alarms and to increase the diagnosis accuracy. In this study, an attempt has been made to improve the diagnosis performance of the CAD systems by incorporating recently developed marine predators algorithm (MPA) in conjunction with three different neural network classifiers including feedforward neural network (FFNN), cascade forward neural network (CFNN), and recurrent neural network (RNN). Unlike other existing studies, fully digital mammogram images from INbreast dataset have been employed for testing of the system proposed in this study. Experimental results reveal that the best classification performance [Accuracy 97.34%, Sensitivity: 98.40%, Specificity: 100.00%] is obtained when MPA is used in conjunction with RNN classifier. To demonstrate the usefulness of the proposed system, the obtained results are compared with the results obtained using already invented CAD systems in previously published studies using the same dataset. The findings suggest that the proposed system is acceptable for real-time clinical applications.

Keywords: Computer-aided diagnosis, Breast masses, Feature selection, Metaheuristic algorithms.

1. Introduction

For many years, cancer has been one of the most serious risks to human life. In both developed and developing countries, breast cancer is one of the most important health challenges. Lung cancer has now been superseded by breast cancer as the leading cause of death among women of all ages, according to recent figures [1]. It is mostly caused by aberrant cells invading over normal cell borders as a result of unregulated growth and division [2]. Breast cancer is distinguished by a variety of anomalies, including breast lumps, microcalcifications, architectural distortions, and bilateral asymmetry. Breast lumps/masses are the most prevalent and potentially hazardous type of abnormality. Breast cancer has already been established to have only one prognosis: timely/early identification [3]. CAD systems based on mammograms are being used as a second reader to assist radiologists in the early detection of breast cancer [4, 5].

Several researchers have already made major contributions in this area and large number of CAD systems have already been proposed in the literature. For instance, Sharma and Khanna [6] (2014) developed a CAD system for detection and classification of masses. Features based on the Zernike moments (ZM) of different orders were extracted and the support vector machine (SVM) classifier was used for breast lesion classification. The proposed CAD system obtained both sensitivity and specificity of 99 % on the image retrieval in medical applications (IRMA) reference dataset, and a sensitivity and specificity of 97 % and 96 % on the digital dataset for screening mammography (DDSM) dataset. Dong [7] (2015) conducted a study for comparing the performances of various classification techniques. Different combinations of shape, texture and intensity features were fed to several classifiers including the random forest (RF), SVM, particle swarm optimization-support vector machine (PSO-SVM) and genetic algorithm-support vector machine (GA-SVM). The proposed system achieved best accuracy of 97.73% with the RF classifier using DDSM dataset. Khan [8] (2016) came up with a CAD system for mass classification by employing the Gabor filter bank. The SVM classifier was employed with Gaussian kernel as a fitness function for PSO. The proposed system achieved average classification accuracy of 93.95±3.85 % for benign and malignant masses using DDSM dataset. Chokri and Farida [9] (2017) proposed a CAD system for breast lesion classification according to two different schemes. In the first scheme masses were classified into four BI-RADS classes (2,3,4,5) and in the second scheme masses were classified as benign and malignant. Multi-layer perceptron (MLP) classifier was used for classification and accuracies of 83.85 % and 88.02 % were achieved using DDSM dataset for two different classification schemes respectively. Kashyap [10] (2018) reported a CAD system for detecting and analysing breast lesions in mammograms. The mass lesions were extracted using the fast fuzzy c-means (FCM) clustering technique. Using textural features, an SVM classifier was utilised to classify the ROIs into mass or non-mass and observed highest sensitivity of 91.76%, specificity of 96.26%, accuracy of 95.46%, and AUC of 96.29% on DDSM dataset and highest sensitivity of 94.63%, specificity of 92.74%, accuracy of 92.02%, and AUC of 95.33% on MIAS dataset respectively. Al-antari [11] (2018) contributed a CAD system for detection, segmentation, and classification of breast masses. The performances of all the three stages were evaluated using the fully digital mammograms from INbreast dataset. You-Only-Look-Once (YOLO), a regional deep learning method, is employed in this study to detect breast mass from full mammograms. The full resolution convolutional network (FrCN), a new deep network model, is introduced and used to segment the mass. Finally, the mass is recognised and classified as benign or malignant using a deep convolutional neural network (CNN). The proposed system achieved 95.64% accuracy for classification stage along with 97.14% sensitivity and 92.41% specificity. Mohanty [12] (2019) employed the forest optimization algorithm to find the best features, and then several classifiers including SVM, k-NN, Nave Bayes (NB), and C4.5 for classification. Experiments were conducted for different hybrid CAD systems developed by using various combinations of computational modules using DDSM and MIAS datasets. In both MIAS and DDSM, the highest classification accuracy of 100 percent is attained for normal vs. abnormal categorization. Hans [13] (2020) proposed an improved version of Harris hawk's algorithm called opposition-based Harris hawk's feature reduction algorithm in conjunction with k-NN and obtained 78.80% classification accuracy using the INbreast dataset. Lbachir [14] (2021) contributed a CAD system for breast lesion diagnosis. Histogram regions analysis-based k-means (HRAK) algorithm was employed for segmentation of breast mass lesions. False positives were reduced using bagged trees classifier. Finally, breast lesions were classified into benign/malignant categories using SVM classifier and classification accuracies of 94.20% and 90.44% were achieved for MIAS and CBIS-DDSM datasets respectively. Sathiyabhama [15] (2021) presented a new CAD system using the grey wolf optimizer (GWO) and rough set theory for mammogram image interpretation. Mass segmented mammogram pictures were used to extract texture, intensity, and shape-based information. A novel dimensionality reduction approach based on GWO with rough set theory was proposed to generate the suitable features subset. The proposed system outperformed other state of the art existing systems and obtained best AUC value of 97.22%. Singh [16] (2022) developed a CAD system for assessing the proficiencies of various texture and geometric features in breast mass classification using the INbreast dataset. Features were ranked by employing relief-F feature selection algorithm and k-NN classifier was used for classification using top nine most discriminative features. The proposed system achieved 90.4% accuracy, 92.0% sensitivity, and 88.0% specificity. Muduli [17] (2022) developed an integrated CAD system that can be used for diagnosis of breast masses from both mammogram and ultrasound images. Exhaustive simulations were performed on mammogram datasets, namely, MIAS, DDSM, and INbreast, as well as ultrasound datasets, namely, BUS-1 and BUS-2 using the proposed CNN based model and achieved accuracies of 96.55%, 90.68%, and 91.28% on MIAS, DDSM, and INbreast datasets, respectively and 100% and 89.73% on BUS-1 and BUS-2 datasets, respectively.

From the detailed analysis of the literature, it has been observed that many researchers have developed various algorithms and techniques for implementing the various phases of the CAD systems using machine learning (ML) and deep learning (DL) based approaches. Due to considerable phenotypic variation in breast masses, a huge number of false positives, and low diagnostic rates, ML based methods have become a contentious issue. During recent few years, the DL based techniques have drawn wide attention from researchers in variety of domains due to their ability of automatic feature computation, feature reduction and classification. Current availability of high-performance computing hardware particularly modern graphical processing units (GPUs) and large-scale datasets have transformed the breast mass categorization challenge. Deeper and wider layers neural networks like CNNs have improved the efficiency and accuracy.

Although DL based CNNs have gained lot of popularity in recent times due to their ability to automatically compute essential contextual features in image classification problems however these techniques also suffer from few limitations. Following issues and challenges have been identified in both ML and DL based techniques for breast mass classification using mammography images:

- It has been found that most of the researchers in literature have used digitized mammogram datasets for experimentation and performance evaluations, very few researchers have used digital mammogram datasets. Most of the datasets are not even publicly shared, due to which it becomes difficult to assess their validity.
- Extraction of meaningful and discriminating characteristics is another difficult problem. Traditional ML algorithms required a handcrafted feature extraction process, which is extremely difficult to develop owing to sample variation.
- DL based techniques often require huge amount of training data for achieving higher classification performances; however, the available mammography datasets are typically sparse.
- DL based techniques also require a lot of computing power particularly modern graphical processing units (GPUs) and extended time periods.

In this paper, an attempt has been made to address all the above-mentioned issues by employing data and computation efficient techniques for breast mass classification. A recurrent neural network (RNN) is a deep learning network architecture that improves the network's performance on current and future inputs by using information from the past. Natural language processing, signal classification, and video analysis are just a few of the applications where RNNs have been demonstrated to be successful. However, in the field of image recognition, RNNs were mostly employed to create picture pixel sequences rather than for complete image recognition [18]. Since RNN's design has grown and become more efficient, it may be worthwhile to investigate whether these remarkable advancements have a direct impact on image classification [19-22].

Keeping these considerations in mind, this study attempted to construct an RNN-based CAD system that can deliver promising classification results in conjunction with newly developed marine predators feature selection algorithm (MPA). The following are the significant contributions of this study:

- Unlike most of the existing studies on breast mass classification, fully field digital mammogram (FFDM) INbreast dataset has been used for testing of the system proposed in this study. Digital datasets are expected to provide a lower noise to signal ratio, a higher detection quantum efficiency, a wider dynamic range, and a higher contrast sensitivity.
- A large set of highly discriminative texture and geometric features has been computed in this study. The issues caused by phenotypic variance of breast lesions among different datasets should be reduced with a huge feature set.
- A recently developed nature inspired metaheuristic MPA optimization algorithm has been tuned to work in conjunction with three different neural network classifiers including feedforward neural network (FFNN), cascade forward neural network (CFNN), and recurrent neural network (RNN) for selection of reduced and pertinent set of features out of the huge set of computed texture and geometric features.
- Numerous experiments have been carried out to exploit the performances of three neural network classifiers in conjunction with MPA feature selection algorithm.

The structure of the remaining paper is as follows: detailed description of dataset and techniques used in this study have been presented in section 2. Section 3 demonstrates the experimental results and discussion of the results. Finally, the paper has been concluded in section 4 along with the directions for future work in this field.

2. Materials and methods

The desired CAD model is illustrated in Fig. 1 below. Usually, traditional CAD models comprise of five phases (pre-processing, segmentation, feature extraction, feature selection and classification) but the proposed model comprises of only four phases. Since the dataset used in this study consists of fully digital mammogram images which do not require any pre-processing hence pre-processing phase has been omitted in this study.

2.1 Mammogram dataset

The intended system was tested and evaluated using the 106 fully digital images from INbreast dataset, which included 115 breast mass lesions in total, out of which 65 were malignant and 50 were benign [23].

2.2 Proposed methodology

2.2.1. Delineation of breast mass from mammogram

Images in INbreast dataset come with ground truth annotations for locating abnormalities in the form of pixel co-ordinates. Since the primary objective of this study is to evaluate the performance of various neural network classifiers and MPA feature optimization algorithm, so no emphasis has been given to image segmentation techniques and breast mass lesions have been delineated using the ground truth annotations along with corresponding ROIs. Readers may refer to our previous publication [16] for getting the detailed information regarding delineation of breast masses using ground truth annotations.

2.2.2. Feature extraction

Textures [24-30] and geometric (shape and/or margin) [6, 31, 32] traits were used to characterize breast lesions in this investigation The multiple texture and geometric models and the count of accompanying attributes extracted in this investigation are presented in Fig. 1. Total 125 texture and geometric traits have been computed in this study. Computed features were normalized using linear scaling to unit range normalization technique [33].

2.2.3. Feature selection

The diagnostic capability of any CAD system may degrade with increase in the size of feature set due to increase in repetitive and irrelevant traits. Furthermore, there are numerous advantages to employing a subset of features rather than all available features in a dataset, such as making data interpretation and visualisation easier, and reducing processing times for complicated and larger datasets [34]. In this study nature inspired Marine Predators metaheuristic algorithm has been employed for feature set reduction

Marine Predators Algorithm (MPA): It is a recently developed optimization algorithm inspired by nature [35]. The fundamental concept of an MPA is that it allows for a flexible switch between two foraging methods, such as Brownian and Lévy motions. The goal of this trade-off is to arrive at the best foraging technique for predators. A combination of two foraging techniques, on the other hand, enhances the rate of encounters between prey and predator in the marine ecosystem. It continues to use

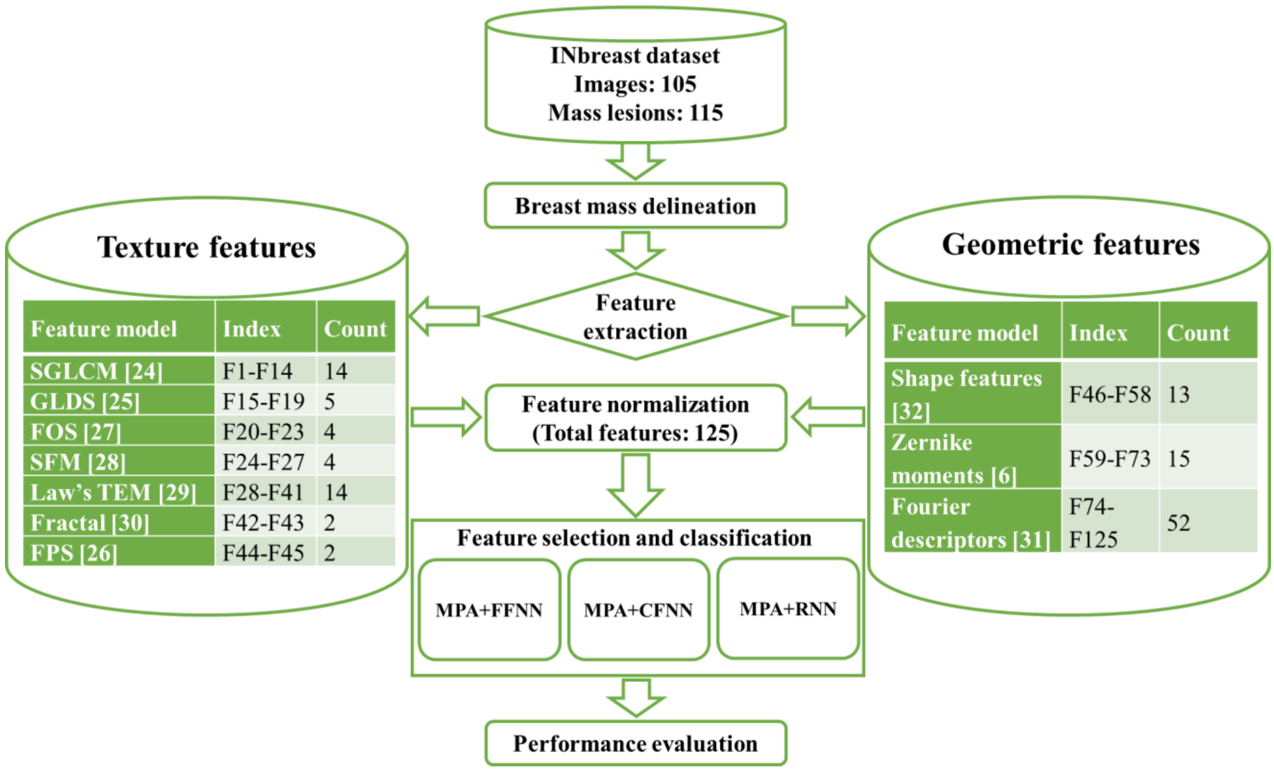


Figure. 1 Visualization of the proposed CAD model

both search strategies until it finds the best option. This method is followed throughout all phases of MPA until the best answer is found.

MPA is a population-based approach, like most metaheuristics, in which the initial solution is uniformly dispersed over the search space as the first trial:

$$X_0 = X_{lb} + \gamma(X_{ub} - X_{lb}) \quad (1)$$

where the lower and upper bounds for variables are X_{lb} and X_{ub}, and γ is a uniform random vector in the range of 0 to 1. Changes in the behaviour of marine predators can also be caused by environmental factors. The impacts of fish aggregating devices (FADs), also known as eddy generation, is one example. When FADs = 0.2, it is likely that FADs will have an impact on the optimization process [36].

MPA employs the survival-of-the-fittest (SOF) principle to select the top predator that can survive for an extended period of time. Every search iteration *(Itr_{max})* in the MPA is separated into three phases: Phase I = up to one third of Itr_{max}, Phase II = in the range between one third of Itr_{max} and two third of Itr_{max}, and Phase III = greater than two third of Itr_{max}.

Phase I: This is the first part of the game, known as the high-velocity phase, in which the predator is supposed to be faster than the prey.

Phase II: This is the unit-velocity phase, in which the predator and prey are both moving at the same speed.

Phase III is the final phase, often known as the low-velocity phase, in which the prey outruns the predator.

Marine predators have an excellent memory for remembering where they have been successful in foraging. In MPA, memory saving simulates this functionality. Each iteration's solution is compared against its counterpart from the previous iteration, and if the current one is better fit, it replaces the prior one. This technique also improves the quality of the solution over time, simulating predators returning to prey-rich areas after successful foraging [28].

Fitness function: Any feature selection approach must include an assessment of the quality of the selected samples. The proposed fitness function regulates the accuracy of the specified attributes. The accuracy obtained will be higher if the features picked in a subset are relevant. The goal of feature selection approaches is to classify things appropriately. The solutions found by MPA must be checked during the iterative process in order to verify the performance of each iteration. The fitness function of the MPA is as follows:

$$fit = \alpha \times er + \beta \times (num\_ft/max\_ft) \quad (2)$$

Where *num_ft* denotes the number of selected features and *max_ft* denotes the maximum number of features. The two parameters α and β denote the significance of classification quality and subset length, respectively. The classification error rate is denoted as *er* and is computed as *(1-acc),* where *acc* is the classification accuracy. For getting the additional detailed information related to MPA algorithm, readers may refer to [35-37].

2.2.4. Classification

Following the selection of significant characteristics, the classifiers are used to evaluate the proposed framework's performance. Classification is the process of assigning a class to a test model based on information gathered by the classifier during training and which classifies unlabelled data samples. Many aspects must be considered when choosing an appropriate classifier, including the computational resources required, the classifier's accuracy over multiple datasets, and the algorithm's performance. This study mainly aims at evaluating the classification performances of three most widely used neural network classifiers including FFNN, CFNN, and RNN. Three measures, such as accuracy, sensitivity, and specificity, are used to evaluate the effectiveness of different neural network classifiers. The classification approaches utilised are described in the subsections below [38].

Feed forward neural network (FFNN): One of the most basic types of artificial neural networks is this one. The data in a FFNN flows via many input nodes before reaching the output node. To put it another way, data only goes in one direction from the first tier to the output node. This is also known as a front propagating wave, and it's normally accomplished with the help of a classifying activation function. There is no back propagation in this sort of neural network, and data only flows in one way. FFNN might have only one layer or several levels. The sum of the inputs' products and their weights is calculated in a FFNN. This is then fed to the output [39-41].

Cascade forward neural network (CFNN): Neurons in CFNN are linked to neurons in previous and subsequent layers. A three-layer CFNN, for example, reflects the direct connections between layer one and layer two, layer two and layer three, and layer one and layer three; that is, neurons in the input and output layers are directly and indirectly connected. These extra connections aid in improving the required relationship's learning speed [42].

Recurrent neural network (RNN): RNNs get their name from the fact that they do the same thing for each element of a sequence, with the outcome being determined by previous calculations (outputs). RNNs can also be thought of as having a "memory" that stores information from past calculations. Because RNN have one or more feedback linkages, neurons can flow in a circle. These RNN properties enable the system to process data in the short term and spot trends. The model learns to predict the outcome of a layer by following this procedure. Each node in the RNN model functions as a memory cell, allowing computation and operation to proceed. The system will collapse if the network's estimation is incorrect. If the network's estimate is incorrect during backpropagation, the system self-learns and keeps trying to make the correct prediction [43].

RNNs are one of the most important subfields of deep learning, which are used to handle sequential input [44, 45]. RNN is inherently deep in time because to the sequential treatment of data. RNN has outperformed other sequence learning algorithms in tasks including language translation and natural language processing. Backpropagation over time is used to train RNNs, however it has the problem of vanishing or exploding gradients. The norm of the back propagated error gradient diminishes exponentially with each time step in a vanishing gradient problem, making it impossible to learn long term dependency in the input sequence. An increasing gradient, on the other hand, causes huge weight updates, making training unstable [21].

3. Results and discussion

This section presents the experimental setup required for assessing the significance of the proposed system along with the detailed analysis and discussion on the obtained results. An attempt has been made in this study to investigate and improve the classification performance of the proposed CAD system for breast mass classification by employing MPA feature selection algorithm and three state of the art neural network classifiers namely FFNN, CFNN, and RNN. All experiments are performed using 106 fully digital mammograms from INbreast dataset containing total 115 mass lesions. The classification results reported in the present work are obtained by using the stratified tenfold cross validation technique. For comparing the performance of different algorithms accuracy, sensitivity and specificity have been used as the performance evaluation measures. The overall percentage of test samples correctly classified by the classifier model is called accuracy. The percentage of actual positives that are correctly identified as malignant is measured by sensitivity, while the percentage of actual negatives that are correctly identified as benign is measured by specificity. These are defined as follows:

$$Accuracy = \frac{(TP+TN)}{(TP+FN+TN+FP)} \times 100 \quad (3)$$

$$Sensitivity = \frac{TP}{(TP+FN)} \times 100 \quad (4)$$

$$Specificity = \frac{TN}{(FP+TN)} \times 100 \quad (5)$$

Here, the terms *TP*, *TN*, *FP*, and *FN* stand for true positive, true negative, false positive, and false negative respectively.

3.1 Evaluation of performances of various neural networks without using feature selection

The primary objective of this study is to investigate the effect of MPA feature selection technique on the performance of three different neural network classifiers and to propose the best combination of feature selection and classification algorithm for breast mass classification. Hence, to exhibit the effect of feature selection on the performance of classifiers, it would be apt to initially perform experiments with complete set of 125 computed features. So, first set of experiments were performed for comparing the classification results of three state of the art neural network classifiers without using the feature selection algorithm. The computed classification results are presented in Table 1 below.

Table 1. Classification results obtained by different neural network classifiers using complete feature set

Feature selection technique	**Processing time (sec)**	**Accuracy (Acc) %**	**Sensitivity (Sn) %**	**Specificity (Sp) %**
FFNN	14.17	89.39	86.15	**94.00**
CFNN	47.14	**92.27**	**93.84**	90.00
RNN	30.65	88.79	89.23	88.00

Table 2. Reduced feature subsets obtained by employing MPA feature selection algorithm in conjunction with different neural networks

Feature selection technique	Count of selected features	Feature index
MPA+FFNN	16	F5, F23, F26, F31, F34, F35, F38, F72, F81, F87, F92, F104, F109, F110, F116, F122
MPA+CFNN	12	F10, F30, F31, F33, F53, F66, F74, F85, F91, F105, F106, F125
MPA+RNN	28	F3, F5, F15, F23, F31, F37, F40, F43, F44, F53, F56, F72, F73, F84, F87, F89, F91, F94, F96, F98, F99, F105, F144, F117, F118, F123, F124, F125

Table 3. Classification results obtained by different neural network classifiers using the reduced feature subsets obtained by employing MPA feature selection algorithm

Feature selection technique	Processing time (sec)	Accuracy (Acc) %	Sensitivity (Sn) %	Specificity (Sp) %
MPA+FFNN	2.32	94.77	96.90	92.00
MPA+CFNN	5.35	93.03	90.76	96.00
MPA+RNN	27.57	**97.34**	**98.40**	**100.00**

From the detailed analysis of results presented in table 1, it has been found that highest classification accuracy of 92.27% is obtained with CFNN classifier. The highest sensitivity value of 93.84% is also obtained with CFNN classifier but the highest specificity value of 94.00% is obtained with FFNN classifier. Since, accuracy and sensitivity values play crucial role in medical image classification problems so, it can be said that best classification results are obtained with CFNN classifier without using the feature selection algorithm. The processing times have also been computed for investigating the effect of feature selection on computation time.

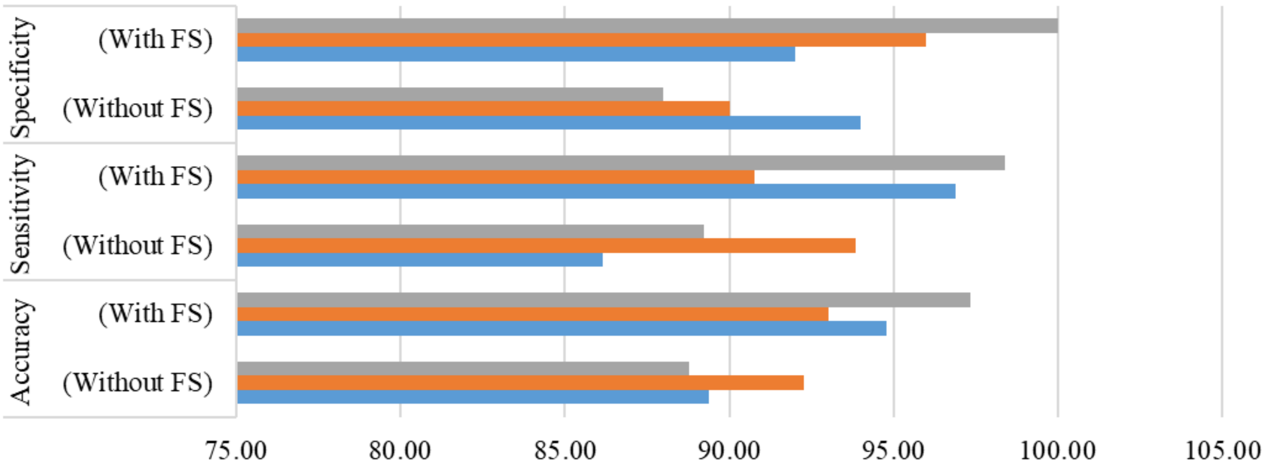
3.2 Evaluation of performances of various neural networks in conjunction with MPA

The second set of experiments were performed for selection of reduced and relevant set of features out of the computed feature set. Nature inspired MPA metaheuristic optimization algorithm has been chosen for selection of reduced and relevant set of features. Since MPA is wrapper-based feature selection algorithm it cannot work independently but works in conjunction with a classifier. In this experiment MPA is employed in conjunction with three neural networks (FFNN, CFNN and RNN) for feature selection. Table 2. Presents the count and the index of the selected features for three combinations of MPA and neural network classifiers. The necessary parameters of MPA have been tuned experimentally in this study.

It can be seen from Table 2 that MPA has reduced the number of features by significant factor for all three neural network classifiers. Further Table 3 presents the classification results when reduced feature subsets selected by three different combinations of MPA and neural networks (MPA+CFNN, MPA+CFNN and MPA+RNN) are used for classification of breast masses by employing respective neural network classifier. The classification results are presented in the form of accuracy, sensitivity, specificity, and processing times. The classification results presented in table 3 clearly shows that MPA algorithm performs best in terms of all three performance metrices [Accuracy 97.34, sensitivity: 98.40, Specificity: 100.00] when used in conjunction with RNN classifier for feature selection and classification task. Further comparative analysis of performances of three neural networks have been carried out by plotting the classification results with and without using the feature selection algorithm in the form of bar chart. Fig. 2 presents the comparison of results in the form of bar chart.

From the detailed comparative analysis, it has been found that although RNN classifier has not performed well with the complete set of computed features but the classification performance of RNN classifier has been improved by large factor when reduced feature set returned by MPA algorithm is used for classification. Although slight reduction in processing time has also been noticed for RNN classifier but the processing time for CFNN classifier is reduced by largest factor on application of feature selection algorithm with least improvement in classification accuracy. Further for demonstration of significance of the proposed system, the obtained results are compared with the results in already published papers for same dataset as shown in Table 4 below.

Received: April 28, 2022. Revised: May 18 2022.



	Accuracy		Sensitivity		Specificity	
	(Without FS)	(With FS)	(Without FS)	(With FS)	(Without FS)	(With FS)
RNN	88.79	97.34	89.23	98.40	88.00	100.00
CFNN	92.27	93.03	93.84	90.76	90.00	96.00
FFNN	89.39	94.77	86.15	96.90	94.00	92.00

RNN CFNN FFNN

Figure. 2 Comparative analysis of the classification performances of different neural network classifiers

Table 4. Comparison with previous work

Reference	Dataset Used	Feature Selection	Classifier Used	Accuracy (Acc) %	Sensitivity (Sn) %	Specificity (Sp) %
Al-antari et al. (2018) [11]	INbreast	-	CNN	95.64	97.14	92.41
Hans et al. (2020) [13]	INbreast	OHHO	k-NN	78.80	-	-
Singh et al. (2022) [16]	INbreast	Relief-F	k-NN	90.40	92.00	88.00
Muduli et al. (2022) [17]	INbreast	-	CNN	91.28	99.43	83.13
Proposed system	INbreast	MPA	RNN	**97.34**	**98.40**	**96.00**

The findings show that the suggested method produced much higher accuracy for the same dataset than previous research. After detailed analysis of all the results presented in this section few following observations have been drawn:

- The newly invented nature inspired MPA optimization performed well when used for feature reduction in the field of breast mass classification as compared to other state of the art feature selection algorithms used in literature.
- Even though deep neural networks, such as CNNs, have lately emerged as a potent machine learning paradigm, their use is limited due to their high processing power and massive training data needs.
- RNNs also belong to category of deep networks that have been originally developed for time-sequence modelling. RNNs have been mostly used in applications like natural language processing (NLP), speech recognition, drug discovery and weather forecasting. Even though very few researchers have employed RNNs for medical image classification in literature, an attempt has been made in this study to investigate the applicability of RNNs in the field of breast mass classification in conjunction with MPA feature selection algorithm.
- Detailed analysis revealed that the classification results obtained by employing MPA algorithm in conjunction with RNN classifier are comparable to those obtained using the CNN classifier. Also, the proposed system has outperformed numerous state-of-the-art machine learning based CAD systems proposed in already published studies and hence the proposed CAD system can be utilised to aid clinicians in the diagnosis of breast masses.

4. Conclusion and future directions

Early detection and diagnosis of breast masses can help in reducing the mortality rate among women. Computer aided diagnosis (CAD) systems have been developed for assisting the radiologists in interpretation of mammogram images and diagnosis of breast abnormalities. In this study, an attempt has been made to exploit the performances of three different neural networks in conjunction with marine predator algorithm (MPA) feature selection algorithm. Experiments have been carried out on 106 fully digital mammogram images from INbreast dataset containing total 115 breast mass lesions. Total 125 traits including 45 texture traits and 80 geometric traits have been computed from the exact breast mass lesions and corresponding ROIs delineated using the ground truth annotations. Comparative analysis of the performances of three different neural network classifiers including feedforward neural network (FFNN), cascade forward neural network (CFNN), and recurrent neural network (RNN) has been carried out in conjunction with MPA feature selection algorithm. Experimental results reveal that best classification performance [Accuracy 97.34, sensitivity: 98.40, Specificity: 100.00] is obtained when RNN classifier is used in conjunction with MPA classifier for feature selection and classification. The performance of the proposed system is also compared with state-of-the-art CAD systems proposed in literature and it has been found that the classification performance of the purposed CAD system is comparable to convolutional neural network (CNN) based CAD systems that require high computational power and large training dataset.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The paper background work, conceptualization, methodology, dataset collection, implementation, result analysis and comparison, preparing and editing draft, visualization have been done by first author and third author. The supervision, review of work and project administration, have been done by second author.

Acknowledgments

We would like to thank the Breast Research Group at University of Porto for developing and sharing the INbreast dataset.

References

[1] H. Sung, J. Ferlay, R. L. Siegel, M. Laversanne, I. Soerjomataram, A. Jemal, and F. Bray, "Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries", *CA. Cancer J. Clin.*, Vol. 0, No. 0, pp. 1-41, 2021.

[2] M. Mustra, M. Grgic, and R. M. Rangayyan, "Review of recent advances in segmentation of the breast boundary and the pectoral muscle in mammograms", *Medical & Biological Engineering & Computing*, Vol. 54, No. 7, pp. 1003-1024, 2016.

[3] A. Oliver, J. Freixenet, J. Marti, E. Perez, J. Pont, E. R. Denton, and R. Zwiggelaar, "A review of automatic mass detection and segmentation in mammographic images", *Medical Image Analysis*, Vol. 14, No. 2, pp. 87-110, 2010.

[4] J. Tang, R. M. Rangayyan, J. Xu, I. E. Naqa, and Y. Yang, "Computer-aided detection and diagnosis of breast cancer with mammography: recent advances", *IEEE Trans. Inf. Technol. Biomed.*, Vol. 13, No. 2, pp. 236-251, 2009.

[5] C. J. Vyborny, M. L. Giger, and R. M. Nishikawa, "Computer-Aided Detection and Diagnosis of Breast Cancer", *Radiologic Clinics of North America*, Vol. 38, No. 4, pp. 725-740, 2000.

[6] S. Sharma and P. Khanna, "Computer-Aided Diagnosis of Malignant Mammograms using Zernike Moments and SVM", *Journal of Digital Imaging*, Vol. 28, No. 1, pp. 77-90, 2014.

[7] M. Dong, X. Lu, Y. Ma, Y. Guo, Y. Ma, and K. Wang, "An Efficient Approach for Automated Mass Segmentation and Classification in Mammograms", *Journal of Digital Imaging*, Vol. 28, No. 5, pp. 613-625, 2015.

[8] S. Khan, M. Hussain, H. Aboalsamh, H. Mathkour, G. Bebis, and M. Zakariah, "Optimized Gabor features for mass classification in mammography", *Applied Soft Computing Journal*, Vol. 44, pp. 267-280, 2016.

[9] F. Chokri and M. H. Farida, "Mammographic mass classification according to Bi-RADS lexicon", *IET Computer Vision*, Vol. 11, No. 3, pp. 189-198, 2017.

[10] K. L. Kashyap, M. K. Bajpai, and P. Khanna, "An efficient algorithm for mass detection and shape analysis of different masses present in digital mammograms", *Multimedia Tools and Applications*, Vol. 77, No. 8, pp. 9249-9269, 2018.

[11] M. A. A. Antari, M. A. A. Masni, M. T. Choi, S. M. Han, and T. S. Kim, "A fully integrated

computer-aided diagnosis system for digital X-ray mammograms via deep learning detection, segmentation, and classification", *International Journal of Medical Informatics*, Vol. 117, pp. 44-54, 2018.

[12] F. Mohanty, S. Rup, B. Dash, B. Majhi, and M. N. S. Swamy, "Mammogram classification using contourlet features with forest optimization-based feature selection approach", *Multimedia Tools and Applications*, Vol. 78, No. 10, pp. 12805-12834, 2019.

[13] R. Hans, H. Kaur, and N. Kaur, "Opposition-based Harris Hawks optimization algorithm for feature selection in breast mass classification", *Journal of Interdisciplinary Mathematics*, Vol. 23, No. 1, pp. 97-106, 2020.

[14] I. A. Lbachir, I. Daoudi, and S. Tallal, "Automatic computer-aided diagnosis system for mass detection and classification in mammography", *Multimedia Tools and Applications*, Vol. 80, No. 6, pp. 9493-9525, 2021.

[15] B. Sathiyabhama, S. U. Kumar, J. Jayanthi, T. Sathiya, A. K. Ilavarasi, V. Yuvarajan, and K. Gopikrishna, "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, 2021.

[16] H. Singh, V. Sharma, and D. Singh, "Comparative analysis of proficiencies of various textures and geometric features in breast mass classification using k-nearest neighbour", *Visual Computing for Industry, Biomedicine, and Art*, Vol. 5, No. 1, p. 3, 2022.

[17] 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, 2022.

[18] R. S. Patil and N. Biradar, "Automated mammogram breast cancer detection using the optimized combination of convolutional and recurrent neural network", *Evolutionary Intelligence*, Vol. 14, No. 4, pp. 1459-1474, 2021.

[19] S. Azizi, S. Bayat, P. Yan, A. Tahmasebi, J. T. Kwak, S. Xu, B. Turkbey, P. Choyke, P. Pinto, B. Wood, P. Mousavi, and P. Abolmaesumi, "Deep recurrent neural networks for prostate cancer detection: Analysis of temporal enhanced ultrasound", *IEEE Transactions on Medical Imaging*, Vol. 37, No. 12, pp. 2695-2703, 2018.

[20] S. S. Begum and D. R. Lakshmi, "Combining optimal wavelet statistical texture and recurrent neural network for tumour detection and classification over MRI", *Multimedia Tools and Applications*, Vol. 79, No. 19-20, pp. 14009-14030, 2020.

[21] B. Chandra and R. K. Sharma, "On improving recurrent neural network for image classification", In: *Proc. of International Joint Conference on Neural Networks*, pp. 1904-1907, 2017.

[22] L. Alzubaidi, J. Zhang, A. J. Humaidi, A. A. Dujaili, Y. Duan, O. A. Shamma, J. Santamaría, M. A. Fadhel, M. A. Amidie, and L. Farhan, "Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions", *Journal of Big Data*, Vol. 8, No. 1, pp. 1-74. 2021.

[23] I. C. Moreira, I. Amaral, I. Domingues, A. Cardoso, M. J. Cardoso, and J. S. Cardoso, "INbreast: Toward a Full-field Digital Mammographic Database", *Academic Radiology*, Vol. 19, No. 2, pp. 236-248, 2012.

[24] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural Features for Image Classification", *IEEE Transactions on Systems, Man and Cybernetics*, Vol. SMC-3, No. 6, pp. 610-621, 1973.

[25] J. S. Weszka, C. R. Dyer, and A. Rosenfeld, "A Comparative Study of Texture Measures for Terrain Classification", *IEEE Transactions on Systems, Man and Cybernetics*, Vol. SMC-6, No. 4, pp. 269-285, 1976.

[26] C. M. Wu, Y. C. Chen, and K. S. Hsieh, "Texture Features for Classification of Ultrasonic Liver Images", *IEEE Transactions on Medical Imaging*, Vol. 11, No. 2, pp. 141-152, 1992.

[27] A. Materka and M. Strzelecki, "Texture Analysis Methods - A Review", *Technical University of Lodz, Institute of Electronics, COST B11 Report, Brussels*, Vol. 10, No. 1.97, p. 4968, 1998.

[28] C. M. Wu and Y. C. Chen, "Statistical feature matrix for texture analysis", *CVGIP: Graphical Models and Image Processing*, Vol. 54, No. 5, pp. 407-419, 1992.

[29] A. S. Setiawan, J. Wesley, and Y. Purnama, "Mammogram Classification using Law 's Texture Energy Measure and Neural Networks", *Procedia - Procedia Computer Science*, Vol. 59, pp. 92-97, 2015.

[30] B. B. Mandelbrot, "The fractal geometry of nature", Vol. 1, New York: WH freeman, 1982.

[31] D. Zhang and G. Lu, "A comparative study of Fourier descriptors for shape representation and retrieval", In: *Proc. of 5th Asian Conference on Computer Vision*, p. 35, 2002.

[32] R. Vairavan, O. Abdullah, P. B. Retnasamy, Z. Sauli, M. M. Shahimin, and V. Retnasamy, "A brief review on breast carcinoma and deliberation on current non-invasive imaging techniques for detection", *Current Medical Imaging Formerly Current Medical Imaging Reviews*, Vol. 15, No. 2, pp. 85-121, 2017.

[33] B. K. Singh, K. Verma, and A. S. Thoke, "Investigations on impact of feature normalization techniques on classifier's performance in breast tumor classification", *International Journal of Computer Applications*, Vol. 116, No. 19, 2015.

[34] Y. B. Wah, N. Ibrahim, H. A. Hamid, S. A. Rahman, and S. Fong, "Feature Selection Methods: Case of Filter and Wrapper Approaches for Maximising Classification Accuracy", *Pertanika Journal of Science & Technology*, Vol. 26, No. 1, 2018.

[35] A. Faramarzi, M. Heidarinejad, S. Mirjalili, and A. H. Gandomi, "Marine Predators Algorithm: A nature-inspired metaheuristic", *Expert Systems with Applications*, Vol. 152, p. 113377, 2020.

[36] D. S. A. Elminaam, A. Nabil, S. A. Ibraheem, and E. H. Houssein, "An Efficient Marine Predators Algorithm for Feature Selection", *IEEE Access*, Vol. 9, pp. 60136-60153, 2021.

[37] M. A. Elaziz, A. A. Ewees, D. Yousri, L. Abualigah, and M. A. A. A. Qaness, "Modified marine predators algorithm for feature selection: case study metabolomics", *Knowledge and Information Systems*, Vol. 64, No. 1, pp. 261-287, 2022.

[38] E. H. Houssein, M. M. Emam, A. A. Ali, and P. N. Suganthan, "Deep and machine learning techniques for medical imaging-based breast cancer: A comprehensive review", *Expert Systems with Applications*, Vol. 167, p. 114161, 2021.

[39] S. Wang, R. V. Rao, P. Chen, Y. Zhang, A. Liu, and L. Wei, "Abnormal breast detection in mammogram images by feed-forward neural network trained by Jaya algorithm", *Fundamenta Informaticae*, Vol. 151, No. 1-4, pp. 191-211, 2017.

[40] M. T. Sadiq, H. Akbari, A. U. Rehman, Z. Nishtar, B. Masood, M. Ghazvini, J. Too, N. Hamedi, and M. K. Kaabar, "Exploiting feature selection and neural network techniques for identification of focal and nonfocal EEG signals in TQWT domain", *Journal of Healthcare Engineering*, 2021.

[41] G. Bebis and M. Georgiopoulos, "Why network size is so important", *IEEE Potentials*, Vol. 13, No. 4, pp. 27-31, 1994.

[42] K. S. Rani and S. Anila, "Comparison of feed forward, Cascade forward and Layer Recurrent Algorithm model for breast cancer prediction", In: *Proc. of IOP Conference Series: Materials Science and Engineering*, Vol. 705, No. 1, p. 012055, 2019.

[43] H. Salehinejad, S. Sankar, J. Barfett, E. Colak, and S. Valaee, "Recent Advances in Recurrent Neural Networks", *arXiv Preprint arXiv:1801.01078*, 2017.

[44] S. M. Awan, M. U. Riaz, and A. Ghaffar, "Prediction of Heart Disease Using Artificial Neural Network", *VFAST Transactions on Software Engineering*, Vol. 6, No. 1, 2018.

[45] S. S. Begum and D. R. Lakshmi, "Combining optimal wavelet statistical texture and recurrent neural network for tumour detection and classification over MRI", *Multimedia Tools and Applications*, Vol. 79, No. 19-20, pp. 14009-14030, 2020.