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An anatomization on breast cancer detection and diagnosis employing multi-layer perceptron neural network (MLP) and Convolutional neural network (CNN)

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This paper aims to review Artificial neural networks, Multi-Layer Perceptron Neural network (MLP) and Convolutional Neural network (CNN) employed to detect breast malignancies for early diagnosis of breast cancer based on their accuracy in order to identify which method is better for the diagnosis of breast cell malignancies. Deep comparison of functioning of each network and its designing is performed and then analysis is done based on the accuracy of diagnosis and classification of breast malignancy by the network to decide which network outperforms the other. CNN is found to give slightly higher accuracy than MLP for diagnosis and detection of breast cancer. There still is the need to carefully analyse and perform a thorough research that uses both these methods on the same data set under same conditions in order identify the architecture that gives better accuracy.

Contents

1. Introduction

Medical science and health research are essential for the survival of all species. It includes researches and information of various diseases, medications, risks and most importantly diagnosis and treatments. Integrating and expanding technology in the field of medicinal science is of prime importance for increasing the capacity and accuracy of disease diagnosis, disease trend and various other factors like treatment[1,11]. In 2018, WHO recorded 9.6 million deaths due to cancer, out of which 6,27,000 deaths were caused due to breast cancer. WHO also suggests early

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diagnosis as a strategic method for treatment and cure of breast cancer. Thus, The application of Neural Network in Breast cancer detection and diagnosis proves to be of immense importance in the field of Oncology (Table 1).

Artificial neural network (ANN) is a sophisticated system that functions closely like the human brain and its nervous system.[59,43,70,16,26] As the brain is also a self-learning organ, so is the artificial neural network system. It performs thousands of iterations and learning to predict outputs based on them. The various nodes of the ANN, are analogous to that of neurons in the human brain.[55,54,49,75] Each node output is taken as the input for the next node after adding a weight function to it.[55,54,53] The learning rate can be modulated for a better accuracy of outputs. For a greater accuracy of output, ANNs perform back propagation, which means it basically performs one round of iterations with a certain set of weights and then it propagates in the backward direction and reduces the errors found in those weights, such that the accuracy of the output after several such forward and backward propagations is extremely high and reliable.[58,57,46]

For complex analysis of data and non-linearity between the input and the predicted output, ANN is a powerful tool of execution of various predictive-output tasks.[76,6,48,50] ANN is a reliable and accurate source for solving problems that have no simple algorithmic solutions[35] like disease prediction and detection. Healthcare has beamingly started applying ANN to various disease detections, analysis and predictions. Analysis of waveforms and signals like that of the Electrocardiogram can be performed using the Kohenen self-organising maps that work based on ANN.[52,55,54] The output of the mapping helps in the interpretation of the waveform.[12,35]. An ANN was also developed for Ophthalmology, that captures images of eye as its input data set and interprets the dysfunctionalities.[27,35] In cardiology, cardiac imaging is used as the input data set for Artificial intelligent network to diagnose cardiac disorders and disease.[10,22]

Table 1
Comparison of accuracy of breast cancer detection from researches that used CNN or MLP architecture for breast cancer diagnosis and classification.

References	Architecture	Sample Size	Apporach	Accuracy	Specificity and Sensitivity
Dabeer et al.[8]	CNN	7009 images from BreakHis dataset	7009 images from BreakHis database is used. Images captured are distributed into 4 magnification levels.	99.86%	Not specified
Sanap and Agrawal[34]	MLP	35 images are used.	Out of 35 tumor images, 17 are used for training and 18 are used for cross validation. DCT extraction feature of MATLAB is used on the data.	On CV dataset: (1) Benign = 72.5% (2) Malignant = 89.00% On training set: 100%	Not specified
Chtihrakkannan et al.[5]	MLP	X ray images are used. Number of images used not specified	Biomarkers of breast tumor obtained from 46 patients.	Average: 89.77% Highest: 96%	Highest sensitivity of 93.22% was obtained.
Kathija et al.[24]	MLP	WBCD,WDBC and WPBC dataset used in 90:10% training: testing ratio. Number of images used not specified.	Wisconsin Breast Cancer Database (WBCD), Wisconsin Diagnostic Breast Cancer (WDBC) and Wisconsin Prognosis Breast Cancer (WPBC) are used in a Training:Testing ratio of 90:10%, with a 10-fold cross validation technique.	WBCD dataset: 98.99% WDBC dataset: 100% WPBC dataset: 100%	WBCD dataset: sensitivity is 0.9844 and specificity is 1. WDBC dataset: sensitivity and specificity is 1 WPBC dataset: sensitivity and specificity is 1
Tan et al.[37]	BCDCNN	322 mammograms from mini-Mammographic Image Ananlysis Society database are used.	322 mammograms from mini-Mammographic Image Ananlysis Society database is used. 2304 parameters and 3 versions are formed. 48*48 input, convolution layer, filter layer and pooling layer in version 3.	Out of the 3 versions, version 3 has the highest accuracy of 82.71%	Version 3 has the highest Sensitivity of 82.68% and it also has the highest Specificity of 82.73%
Guan and Loew[18]	CNN	322 mammograms from Mammographic Image Ananlysis Society database (MIAS) and 2620 images from Digital database for Screening Mammograms (DDSM) are used.	322 mammograms from Mammographic Image Ananlysis Society database (MIAS) and 2620 images from Digital database for Screening Mammograms (DDSM) are used. Pre training is done using VGG-16 model for transfer learning. Convolution layer is of 3*3 pixels. Max pooling layers, 16 hidden layers and 13 convolutional layers and 3 FC layers are used.	90.5 ± 3.2	Not discussed
Mojarad et al.[30]	MLP	Biomarkers of breast tumor obtained from 46 patients.	Breast tumor biomarkers are obtained from 46 patients diagnosed with carcinoma or benign breast tumor. 4 biomarkers used are DNA ploidy, cell cycle distribution (G0G1/G2M), steriod ploidy and S-phase fraction. Updation of input data using Hessian Matrix. K-fold cross validation is performed.	All 4 markers: 63.04% ER/PR & G0G1/G2M: 63.04% All markers except DNA ploidy: 63.04% SPF marker: 65.21%	Sensitivity: All 4 markers:43.58% All markers except DNA ploidy:43.58% ER/PR & G0G1/G2M: 33.33% SPF marker: 33.33% Specificity: All 4 markers:75.40% All markers except DNA ploidy:75.40% ER/PR & G0G1/G2M:81.96% SPF marker:85.24%

Table 1 (*continued*)

References	Architecture	Sample Size	Apporach	Accuracy	Specificity and Sensitivity
Kiyan and Yildirim[60,25]	MLP	699 samples from the Wisconsin breast cancer dataset are used	699 samples from the Wisconsin breast cancer dataset is used, half of it was used for training. The breasts are classified on 9 attributes into 2 values in the class variable of breast cancer: benign (non-cancerous) and malignant (cancerous). Neural networks RBF, GRNN, PNN and MLP were applied on it.	Performance by:RBF (Radial Basis Functions) = 96.18%PNN (Probabilistic Neural Networks) 97.0%GRNN (Generalized Regression NeuralNetworks) = 98.8% MLP was found to to give a performance of 95.74%	Not discussed
Nrea et al.[61]	CNN	1588 full mammogram images are used.	1588 full mammogram images with mass abnormalities are used as dataset for the setup. 80% of the dataset was used for training, 10% for validation and the remaining 10% for testing. 5 convolutional layer CNN model with each convolution layer is followed by Relu activation layer, batch normalization, maxpooling layer and dropout except the second layer which has neither dropout nor maxpooling was employed to classify the dataset into benign or malignant abnormality in mammogram(MG) images	The detection accuracy of the CNN model is found to be 91.86%.	Sensitivity : 94.67% Specificity: 89.69%
Bardou et al.[62]	CNN	BreaKHis dataset of 7909 breast images is used.	BreaKHis dataset of 7909 breast images is used and it comprises of 8 types of benign and malignant tumors. 25% of the training data is used for cross validation. A 5 CNN layer topology with 3*3 filters and 2 fully connected layers is employed to classify the dataset. RELU layer is also applied.	Accuracy between 96.15% and 98.33% is achieved for the binary classification and 83.31% and 88.23% is achieved for multi-class classification.	Not specified
Hassanien et al.[63]	MLP	25 breast images are used.	It employs adaptive ant-based clustering to identify breast malignancy in 25 breast images with 135 objects and then an MLP NN to evaluate and classify it into Benign and malignant samples. 90 samples were used for training and 46 were used for testing.	On an average, The AntClust gave an accuracy of 90.70% accuracy of MLPNN is given to be 98%	Not discussed
Ibrahim et al.[64]	MLP	WDBC dataset with 699 patterns is used	Uses MLP with multi-objective differential evolution technique and reduces the error rate. Breast Cancer Wisconsin Dataset consisting of 699 patterns is used with 9 input attributes in a basic 3 klayer MLP structure.	Average training accuraccy was found to be 97.53% Average testing accuracy was found to be 97.51%	Sensitivity of the proposed method: 97.74% Specificity of the proposed method: 97.07%
Shargabi et al.[65]	MLP	Sample size is not specified	A tuned MLP that is categorized into two, one investigates the reduction of the extracted feature size, while the other investigates the enhancement of the classification power. WDBC dataset was used for carrying out the research.	Accuracy of 97.70% was obtained	Not specified
Iesmantas and Alzbutas[66]	CNN	400 Hematoxylin and Eosin (H&E) stained breast histology microscopy images are used.	400 Hematoxylin and Eosin (H&E) stained breast histology microscopy images were used in a CNN with each image labelled into 4 classes: normal tissue, benign lesion, *in situ* carcinoma and invasive carcinoma. Convolutional Capsule network which is a modified CNN network is used.	Cross validation accuracy of 87% is obtained with a high sensitivity	Not discussed

Artificial intelligence has been implemented into the medical field of oncology as well.[46,51,56] In fact, for skin cancer, a deep learning algorithm is formulated that uses images of various skin malignancies and classify it into the subtype of skin cancer. And it was proved to be quite accurate.[13]. Cervical cancer is an extremely common cancer among Women and is a major life taking disease as well.[3] A PAP smear test that examines the uterine cells for malignancy is required for early detection and for possible cure of the cervical cancer. Traditionally, the cell examination is done under a microscope by human eye, which may call for a certain human error. So, as an easier approach, a neural network-based program, called PAPnet has been devised. This network examines the smears and is known to give a higher accuracy than the traditional methodology.[35] Ovarian cancer has also been attempted to be detected using an artificial neural network.[40] Lung cancer also causes a high number of deaths as compared to other cancers in the world. Traditionally detected using Computer Tomography (CT) scans but a better technology to detect lung cancer in its early stages is the need of the hour.[29] Computer analysis of chest radiographs is performed so as to ease the extreme challenges faced in classifying the examination results upon traditional means.[77] More recently, the images of CT scans are processed and classified using Neural Networks.[29] An artificial neural network procedure also called Neural Embedded based Detection procedure identifies the cancer cells upon diagnosis for early detection of lung cancer upon examination of the images of specimen.[42] ANN is also employed for early detection of prostate cancer and is found to have a high accuracy of prediction than the conventional PSA parameters.

The most common type of cancer in Women is found to be Breast cancer.[4] It can be detected upon physical examination, biopsy or mammography. Biopsy is an expensive, intrusive and stressful approach to breast cancer detection.[47,44] So in order to surpass these disadvantages, an ANN is developed to take input as radiological finding and generate output analogous to conventional Biopsy.[14] A simple neural network can be employed in order to detect and predict the probability of malignancy in breast masses.[45] Under one such approach, breast abnormalities are detected in digital mammograms using a Particle Swarm Optimized Wavelet Neural Network (PSOWNN) that uses mammograms as its input set form the algorithm in order to classify the suspicious regions in breast masses.[9] A convolution neural network has also been used in order to classify breast cancer histology images in order to provide early detection of breast cancer at low cost and high accuracy. A feed forward neural network can also be devised to statistically diagnose breast cancer with a very high accuracy.[60,25] In another similar but advanced approach, both association rules and ANN are used for detection and classification of Breast cancer. Association rules are employed to reduce the dimension of the database of breasts and is classified by a Neural network.[23] Upon comparison of various techniques of Artificial intelligence like multilayer perceptron neural network (MLPNN), combined neural network (CNN), probabilistic neural network (PNN), recurrent neural network (RNN) and support vector machine (SVM) for diagnoses of Breast cancer, Support vector machine (SVM) was found to be the best approach in terms of accuracy and performance.[46]

2. Neural network for breast cancer diagnosis and classification

Application of neural networks in breast cancer detection has a major advantage over traditional methods in terms of time taken for examination. Where conventional methods take up a large amount of time in examination of one data at a time, ANN examines a large amount of data after a short training period. ANNs predict outputs with a high accuracy and are easy to code. Whereas traditionally, predicting outputs in medicine takes years of experience and knowledge in the particular field. Plus, various types of ANNs can be developed in order to diagnose breast cancer, which broadens the horizons for earlier and easier breast cancer detection.

A Multilayer Perceptron Neural Network is a Neural Network of the feed forward type. It uses the Backpropagation technique for learning. It has an input layer of neurons that act as receivers, one or more hidden layers of neurons that compute the data and undergo iterations and then the output layer which predicts the output (Fig. 1).

Ayer et al.[2] discussed a three-layer ANNs that examines256 mammogram images and classifies them. Micro calcification of samples into size ranges of 50–250 μm, 100–500 μm, 200–1,000 μm, and 400–2,000 μm was used to formulate the network. The classification based of malignancy size range was achieved using four ANNs. The ML-NN was found to be 84% sensitive at 75% specificity.

Ting and Sim[38] implemented a supervised multilayer neural network in classification of breast cancer in order to assist medical examiners. They considered 170 mammograms that have already been tested of malignancies as image input set. Upon using these in an ML-NN, the neural network successfully classified the breast malignancies. Based on the intensity of malignancy, the three classifications were, benign, malignant and normal. When compared with the known malignancy of the input data used, they found the accuracy of the ML-NN to be 90.59% and its sensitivity to be 90.53%.

Fogel et al.[15] compared two constructions of ML-NN for diagnosis of breast cancer by conducting two experiments using 400 image sets of mammograms of patients for training the ANN and 283 mammograms for testing the networks. One experiment used one 9-2-1 multilayer perceptron network (9 input neurons, 2 hidden neurons and 1 output neuron) and the other experiment was performed using a 9-9-1 multilayer perceptron network. 5 trials were performed in each experiment and the results of mean squared errors and correctness were tabulated. They found that the 9-9-1 ML-NN gives up to 97.9% correctness at the most and the 9-2-1 ML-NN gives a correctness of up to 98.6% at the most. Thus, they concluded that the 9-2-1 ML-NN gives higher accuracy and is an optimized design.

In another approach involving ML-NN, Floyd et al.[14] applied back-propagation on a Multi-layer neural network with a single hidden layer, to predict breast malignancy. Eight parameters of breast mammograms namely, mass size, asymmetric distortion, mass margin, architectural distortion, calcification number, calcification morphology, and calcification density and calcification distribution were taken as input for the ML-NN. The network was trained on and classifies 259 cases using known outcomes from radiologists. Once it was trained, the weights were kept stagnant in order to test the network. One test case was evaluated and then put back into the network and another case was used to test, until

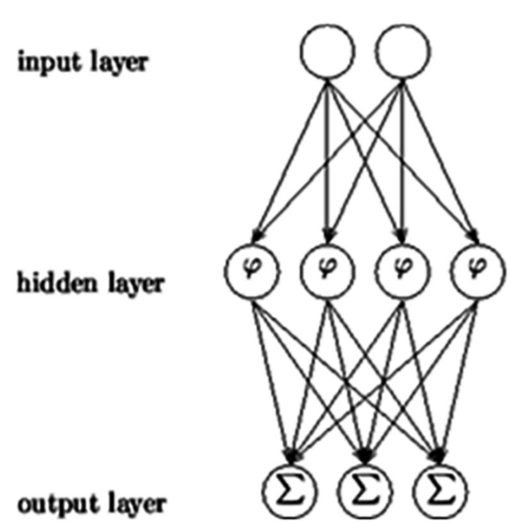

Fig. 1. Architecture of a Multi-Layer perceptron Neural Network.[38.]

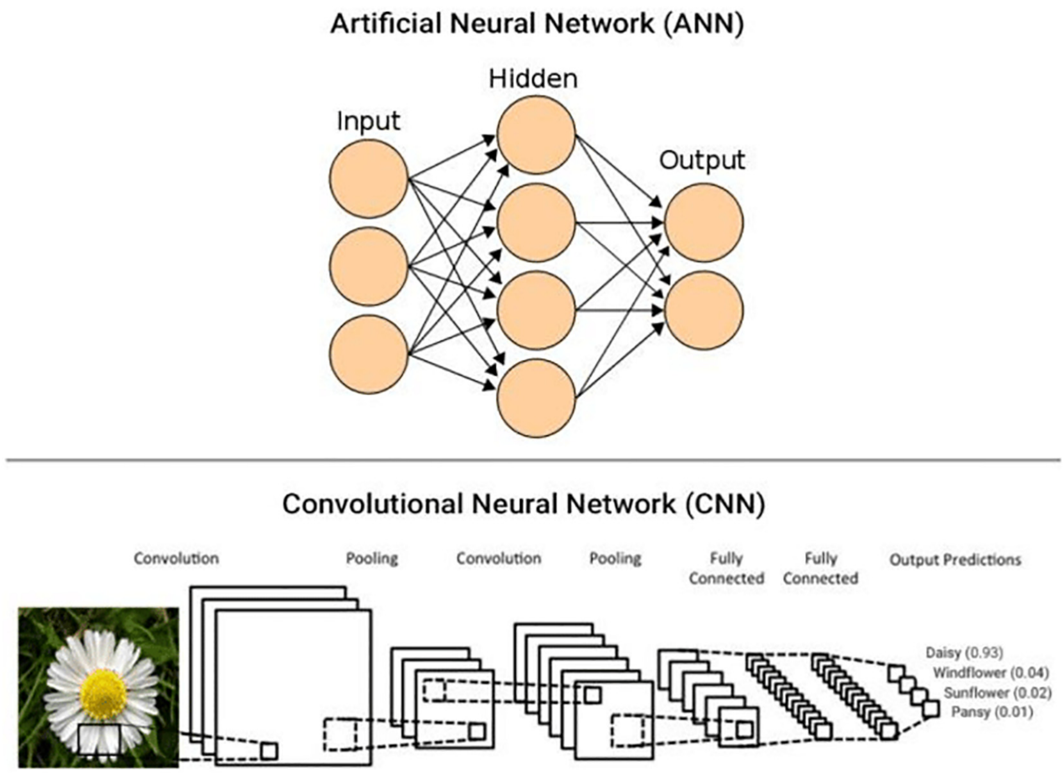

Fig. 2. Architecture of a Convolutional neural network and working of CNN used to classify a flower into 4 types.[78]

all 260 cases were used to test the design. This back propagation was performed in order to improve the accuracy of prediction of output. The network classified the output into biopsy benign and biopsy malignant. The best output from this design was found when at 0.1 threshold value; the network identified 99 out of 168 benign cases and 92 out of 92 malignant cases.

In order to determine the best activation function to be used in a multilayer neural network, Isa et al.[20] used different activation functions in an MLP, to detect and classify breast cells. They used back propagation to train the ML-NN. Upon comparing the output accuracy, MLP having a hyperbolic tangential activation function produces high accuracy than sigmoid, sinusoidal, exponential and neuronal logarithmic activation functions. The accuracy in detecting and classifying the breast cells was found to be 97.0% when hyperbolic tangential function was used. Thus, hyperbolic tangential function was found to be the most efficient and apt activation function to be used in an MLP.

Meinel et al.[28] used a back propagation neural network to create a Computer Aided Diagnosis system that enhances Magnetic Resonance images of breasts. 80 lesions were used for the procedure, out of which 43 were malignant and 37 were benign. Image parameters for the NN were fixed and 13 input features were chosen from 42 different ones. The network was trained to distinguish and enhance the lesion from the background. They found that CAD systems improve the MRI by enhancing it, making it easier and increasing efficiency to detect disorders in it.

Cedeño et al[78] devised a neural network called, Artificial Metaplasticity Multi-Layer Perceptron. Artificial metaplasticity was used in order to minimise error. It was implemented in a Multilayer perceptron neural network to detect breast malignancy. The network was trained using 410 samples of breast images, of which 144 were malignant and 266 were benign. To test the system, 233 samples consisting of 95 malignant and 178 benign samples were used. The AMMLP network output accuracy and sensitivity was compared to the conventional methods of CAD that use Back propagation NN. The result was found to have 99.26% accuracy, 97.89% specificity and 100% sensitivity, proving it to be better than conventional back propagation NN.

Raad et al.[31] compared a Radial Basis Function (RBF) kernel to the MLP neural network in classifying breast masses to diagnose breast cancer. 9 attributes including both patient information like id and breast characteristics like size were taken as the input parameters. The MLP had 5 neurons in the hidden layer and 2 output neurons. The output neurons gave the values of either 0 (benign) or 1 (malignant) in order to classify the breasts. 683 cases were taken from a breast database. Upon comparing the MLP with RBF, MLP was found to give 88% of correctness, whereas RBF was found to give 97% of correctness. This implies that RBF is a more efficient method to detect breast cancer when compared to MLP.

Another comparison of various neural network models was performed by Janghel et al.[21]. The comparison was based on True positive rate (TPR), True negative rate (TNR), accuracy (AC), false negative rate (FNR) and false positive rate (FPR). The comparison was made between Multilayer perceptron using Back Propagation Algorithm, Radial Basis Function Networks, Learning vector Quantization and Competitive Learning Network. 10 input attributes (like Clump Thickness, Uniformity of Cell Size, Uniformity of Cell Shape, Marginal Adhesion, Clump Thickness, Single Epithelial Cell Size Bare Nuclei, Bland Chromatin, Normal Nucleoli and Mitoses) were considered. Out of 699 patient databases taken into consideration, 458 are benign cases and 241 are malignant cases. 444 were used for training which includes 260 benign cases and 184 malignant cases. Then, 239 cases were used for testing which contains 184 benign and 55 malignant cases. Upon stimulating this data in the considered models, MLP containing 1 hidden layer of 25 neurons was found to have 51.88% accuracy at the most. The RBF model had 49.79% accuracy, LVQ model had 95.82% accuracy and the CL model had an accuracy of 74.48%. In conclusion, LVQ model

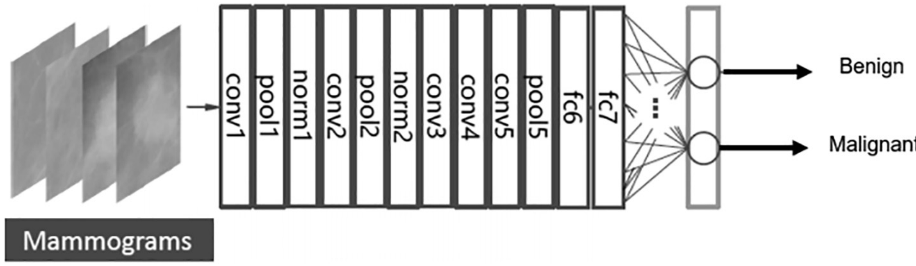

Fig. 3. Process flow for breast cancer detection and classification using CNN architecture.[32.]

was found to be the most accurate in order to predict breast cancer, followed by CL, MLP and then RBF models.

3. Convolutional neural network for breast cancer diagnosis and classification

Convolution Neural Network (CNN) is a neural network class mostly employed to examine, identify or classify images as it simplifies the images for better analysis. This network is advantageous as it needs fewer human efforts and pre-processing. Back propagation is also included in the learning process to make the network more accurate. In terms of design, it is closely related to MLP, as it consists of an input layer of neurons, multiple hidden layers and an output layer. Each neuron in one layer is connected to every neuron in the succeeding layer. The image (say, a flower) to be classified or analysed is passed through multiple layers. The convolution layer is used to filter the image upon performing convolution in order to enhance the features. Then, pooling layer down samples (reduces the sample size) of the sample of features extracted. This makes the processing faster, as the parameters decrease. Max pooling takes the maximum quantity obtained upon pooling and Average pooling takes the average of the pooling output. In CNN, an activation function called Rectified Linear Unit is used to ensure non linearity. Then after passing through a fully connected layer, the output is predicted into classes (for classifying a flower, the classes may be daisy, windflower, sunflower, pansy) (Fig. 2). This network frame is increasingly being used in image processing as it solves the signal transition problem and accurately extracts features.

The CNN architecture has been employed in breast cancer diagnosis and classification because of its ability of feature extraction that can be used to enhance and easily see malignancy in breast masses. Thus, aiding in the process of early detection of breast cancer, so that it can be treated at a lower stage, before it spreads more.

Wang et al.[39] devised a Max-pooling based convolution neural network to detect mitosis in breast images. The examination was performed on a small dataset. They considered a data set of 50 images and used a CNN with a series of convolution and pooling layers. 2D convolution was performed with a rectangular filter. This network was trained to pixelate the image and classify each pixel in it. A fully connected layer classifies the image into either mitosis (mitotic nuclei) or non-mitosis (non-mitotic nuclei).

Rakhlin et al.[33] used data augmentation in a deep neural network to classify breast masses to diagnose breast cancer. 400 Haematological and Eosin (H&E) stained images were considered for the execution of this trial. The images consisted of 2048*1536 pixels. The image was to be classified into 4 classes, normal, benign, *in situ* carcinoma and invasive carcinoma. Deep convolution feature representation network is employed to take a large image dataset and give a better output prediction. Data pre-processing and augmentation is then done. 50 random colour augmentations are performed on each image, to enable improved quantitative analysis of microscopic images. The image is then downscaled and cropped after staining normalization. The fully connected layer is removed from the CNN to incorporate images of random size. Further, feature extraction is performed. 10 gradient boosting models are trained per fold. Average of predictions over all augmentations and models is calculated and then the predicted class is extracted by maximum probability score. This is the 10-fold cross validation method. For 2 class (non-carcinomas and carcinomas) classification the network gives an accuracy of 93.8 ± 2.3%. For a 4 class (normal, benign, *in situ* carcinoma and invasive carcinoma) the accuracy was found to be 87.2 ± 2.6%.

Cireşan et al.[7] suggested a technique to detect mitosis in breast cancer involving deep neural network. The aim is to classify each pixel into 2 classes, mitosis and non-mitosis. A feed forward DNN is used. 50 images are used as input and are pixelated. In each pixel, a square image window is used having RGB values that predict the class of the pixel. A series of convolution and max pooling layers are employed in the set up of the DNN. Convolution layer has a rectangular filter and performs 2D convolution. The design also has some fully connected layers that mix the output into feature vector that is then used to extract features from the input in order to classify it. The predicted output was then classified into mitosis or non-mitosis.

Ragab et al.[32] used a deep convolution neural network called AlexNet, to classify breast mammography images into two classes. This network had 5 convolution layers, 3 pooling layers and 2 fully connected layers (Fig. 3). In order to obtain high accuracy, large input data set needs to be used for training a NN, but due to availability of only limited datasets, data augmentation is used in order to increase the size of input. In this case, rotation method of augmentation was used. Firstly, the input image was converted to greyscale and consecutively to binary image using the threshold technique. Then, the number of pixels is counted and the largest binary object is labelled as tumorous. The largest area pixels indicated by 1 are tumorous and the rest is indicated by 0 and is non-tumorous. Upon multiplying the input image and the binary image, the final output image is obtained. The accuracy of this algorithm is found to be 71.01% and using SVM increased the accuracy to 87.2%.

Huynhet al.[19] also devised a CNN that utilizes the AlexNet architecture. AlexNet eliminates the need of segmentation. 219 breast lesions were taken into consideration and the 5-fold-cross validation method as applied to extract features directly from the input image. Also, the method of soft voting was also chosen for a more simplistic approach. Transfer learning methods are employed in order to increase efficiency and accuracy even when a small dataset of images is used. A CNN with convolutional layer, pooling layer and fully connected layers was employed in order to classify the breast masses in to benign and malignant cases. Thus, the experiment concluded that the use of CNN having AlexNet can facilitate computer-based diagnosis of breast masses.

Lévy and Jain[26] compared a baseline model of CNN, AlexNet and GoogLeNet architectures of CNN employed to detect mitosis in breast cells. The model of AlexNet and GoogLeNet was modified as the last fully connected layer was replaced to the output class. Additionally, in the GoogLeNet the training was hindered by two auxiliary classifiers, thus they were also eliminated. They used a public dataset from Digital Database for Screening Mammography (DDSM). 1820 images from 997 patients were considered for this process. The images are divided into training set (80%), validation set (10%) and testing set (10%). The input image used was of size 224*224*3. 3*3 convolution layer with a ReLu activation function and max pooling is employed. For a shallow CNN, 3 fully connected layers of size 128, 64 and 2 are used and two soft max layers for binary classification are used. The base learning is $10^{(-3)}$ with a batch size of 64. Weight initialization is then done. In AlexNet, convolution layer is initialized with pre-trained weights and a smaller learning rate multiplier of 0.1. The three fully connected layers are initialized randomly. Dropout rate is 0.5 and base learning rate is $10^{(-3)}$. It is trained with Adam. For GoogLeNet, weight initialization is the same as AlexNet. Learning rate multiplier is 0.1 before Inception_5a module, 1 for Inception_5a and Incception_5b module and lastly, 10 for the last fully connected layer for more aggressive learning. It is trained with Vanilla SGD. Base learning rate is $10^{(-3)}$ dropout rate is 0.2. For each image in the training set, rotation, cropping and mirroring transformation is done in order to increase the effective size of dataset. Masses and their diagnosis is invariant to these transformation. The result found that GoogLeNet is the best among the architectures compared and suitable for fine tuning and less prone to overfitting. The accuracy of GoogLeNet is 0.929, when baseline architecture has the accuracy of 0.604 and AlexNet has the accuracy of 0.890.

Xie et al.[41] devised a CNN based on regression model architecture for the detection of mitosis in breast cells. The model consisted of a CNN with two convolution layers, two max pooling layers followed by three fully connected layers. For better result and precision, the first convolution layer has a filter of size 6*6 and the second one has a 3*3 filter size. The model is modified by replacing the last layer with a structured regression layer to encode topological information. Regression on proposed structured proximity space is performed for patches in order for the centre of each image to get a value higher than its neighbours. A proximity patch is generated to help detect the cell centre precisely. Then, under the final proximity mapping for the testing image all the proximity patches are fused together. Sigmoid function is used as the activation function for the last fully connected layer while ReLu function is used for thee other convolution and fully connected layers. This is performed at a learning rate of 0.0005 and dropout rate of 0.2 for the fully connected layer. Three datasets are used, first being the TCGA dataset from which 32, 400*400H&E stained microscopy images are considered and magnified 40 times. This is the one we will consider for the review as the other two sets are of cervical cancer cells and neuro-endocrine tumor cells. The result had a precision of 0.919 for the breast mitosis detection under the regressive CNN model.

Sun et al.[36] used an approach called semi supervised learning (SSL) in CNN which was based on graphs. The diagnosis system consisted of data weighing, feature selection, dividing co-training data labelling and CNN. Out of 1874 pairs of breast images 3158 regions of interest (ROI) were selected of which 100 was labelled data and 2300 was unlabelled data and 758 ROIs were used for testing. The accuracy of the CNN was found to be 0.8243 using labelled and unlabelled data. In this methodology the idea was to initially use a small amount of labelled data and then add large amount of unlabelled data. For each mass, 21 computational features were considered. Each convolution layer is followed by a max pooling layer and the CNN ends with a fully connected layer. The learning rate is 0.1 for 100 epochs, batch size for input is 100 m and sub-sampling rate is 2. Each image is resized to be 52*52 pixels. Training images are augmented; rotated and mirrored after data augmentation each image generates 8 images. For data weighing, Exponential function, Gaussian function and Laplacian function are compared. The result shows that Exponential function gives high sensitivity, specificity, and highest accuracy of 82.43% among others.

Geras et al.[17] devised a CNN to analyse its performance with various features like input resolution and number of training sets. 129,208 patient's mammograms were used. 80% of it was divided into disjoint training set, 10% of it was used for validation and the remaining 10% was used as test sets. Next, the images were cropped to 2600*2000 pixels. The input data was then augmented. The CNN consisted of convolution layer, followed by max pooling layer and then a fully connected layer. After convolution layers, a rectifier function was applied. The data was trained on the training set and then the resolution was varied and then again the output was validated. The result showed that the performance of the system improved with the increase in the number of training sets and it also increases with the increase in input resolution. When measured by output entropy, the prediction was found to be more accurate and confident. The accuracy of the model was also compared to the accuracy of radiologists in predicting breast malignancy. The accuracy of the radiologists was found to be 0.704 while the accuracy of the model was 0.688, which is extremely close.

Mehdy et al.[68] performed a similar comparative study of various Artificial Neural Networks to diagnose and classify breast cancer. 4 medical applications of ANN namely mammogram, ultrasound, and thermal and MRI imaging are deeply analysed with various methods like SOM, CNN and MLP. These techniques to diagnose breast cancer are discussed and tabulated. It can be concluded by studying this table that CNN outperforms MLP. The tabulated accuracy makes it clear that CNN has a better accuracy of diagnosing and classifying breast malignancy than MLP.

Tello-Mijares et al.[69] also compared the performance of CNN with tree random forest (TRF), multilayer perception (MLP), and Bayes network (BN). Image pre-processing RGB and grey input, image denoising, and curvature function for initial elliptical points for the GVF and classification and then feature extraction is performed stage wise for each thermographic breast image from the dataset of 63 thermographic images out of which are 35 normal and 28 are abnormal in RGB colour format and in JPEG image format with a size of $680 \times 480 \times 3$. In the CNN, 277*277*3 RGB images are used. While the accuracy of MLP was found to be 88.88%, the accuracy given by CNN was found to be 100%, which was also better than TRF and BN. Thus, CNN proved to be better than the other ANN algorithms in terms of accuracy of diagnosis and classification of breast cancer. They also claimed CNN is robust and efficient for the purpose of breast cancer detection when combined with GVF.

In their study Shahnaz et al.[67] compared Bayes, SVM, Logistic Regression, KNN, Random Forest, MLP and CNN classifiers to diagnose and detect breast malignancy.

The Wisconsin Breast Cancer Database was used in each classifier that contained 699 images and 11 attributes. They analysed the data into 30 attributes with 569 useful data. After using this data into each algorithm, it was classified into malignant and benign classes. Upon comparison at batch size 100 and learning rate of 0.03, MLP gave the maximum accuracy of 97.891% in layer 5 at 100 epochs while CNN gave the maximum accuracy of 98.06% for 300 feature maps and at 1000 epochs. Thus, CNN gave a greater accuracy of diagnosis than MLP under similar conditions and can be said to be better than MLP for the same reason.

3.1. Classifying subtypes of cancer

Classification of breast cancer into its subtypes is an important aspect of ANN. Gao et al.[72] suggested a method called DeepCC (deep cancer subtype classification) for molecular level of cancer subtyping. In this method, 14 independent CRC datasets involving 3578 primary tumor samples are used. For each individual sample, DeepCC calculates the functional spectrum. Functional spectrum is grained using linear regression. DeepCC was implemented on MXNet with optimization techniques to classify subtypes of cancer. A correlation is found between deep features and functional gene sets. 10 deep features were visualised in a 2D space. DeepCC classifier and single sampe predictor both had higher accuracy, sensitivity and specificity than methods like random forests (RF), support vector machine (SVM), gradient boosting machine (GBM), and multinomial logistic regression algorithms for subtyping of breast cancer.

In an hybrid model, Rhee et al.[73] used CNN for breast cancer subtype classification. The method was a graph-based approach. The first step of the method is the graph convolution step to represent and capture localized patterns of the graph nodes (genes). The second step is the relational reasoning step. In this step, the model learns the complex association between graph node groups from the learned localized patterns of graph nodes in the previous step. The next step is to merge the representation of graph convolution layer and relation reasoning layer. This method was employed on a real dataset of 57,292 genes of human breast cancer patient samples. These are classified into the subtypes Luminal A, Luminal B, Basal-like, and HER2. The proposed method gave the highest accuracy of classification of 86.29% when compared to other ANN algorithms. Thus, it concluded to be a successful method of molecular classification of breast cancer.

Couture et al.[71] used deep learning to predict breast cancer histological and intrinsic subtypes. 1203 patient's data was selected from the Carolina Breast Cancer study, for training and testing. Tumor tissue microarray construction was performed on the dataset. Based on the highest Pearson correlation with a subtype-defined centroid, each tumor was categorized into one of five intrinsic subtypes (Luminal A, Luminal B, HER2, Basal-like, Normal-like), using the 50 gene, PAM50 signature. Image analysis was done of the dataset. High accuracy classification into subtypes was seen by this method.

Thus, in conclusion, CNN can be used and modified for classification of breast cancer into its subtypes.

3.2. Comparison of MLP and CNN

Übeyli[74] compared the classification accuracies for breast cancer for different ANN algorithms namely multilayer perceptron neural network (MLPNN), combined neural network (CNN), probabilistic neural network (PNN), recurrent neural network (RNN) and support vector machine (SVM) in order to identify the best and the most optimum diagnostic approach. The Wisconsin breast cancer dataset was studied and 683 records were analysed under each algorithm. Malignancy was confirmed by performing biopsy on the breast tissue. Between MLP and CNN, MLP had a sensitivity of 91.19%, specificity of 92.34% and accuracy of classification was 91.92%, whereas, CNN showed much higher rates of sensitivity (96.86%), specificity (87.81%) and accuracy (97.46%). This showed that CNN was better than MLP as a breast cancer detection algorithm.

Shahnaz et al.[67] compared Naive Bayes, SVM, Logistic Regression, KNN, Random Forest Neural Network, MLP and CNN classifiers for breast cancer detection. The Wisconsin dataset with 11 attributes and 699 instances was used. The classification was done into benign and malignant breasts. The data was analysed to come up with 30 attributes. At 300 feature maps, 100 batch size, 0.03 learning rate and 1000 epoch size, the accuracy of CNN was the highest at 98.06%, while the highest MPL achieved was 97.891 at five layers,100 training time and 0.03 learning rate. This again shows that CNN is better at breast cancer detection than MLP.

4. Challenges and future scope

The cancer cases reported every year in India are increasing and the use of ANN for cancer diagnosis can ease this burden while also improving the efficiency of healthcare systems too.

Use of Artificial intelligence and neural networks for breast cancer diagnosis can improve detection of breast cancer cells, help lower the chances of errors in detection and minimise the time taken for diagnosis by manual methods. These result in a higher survival rate. The average 5-year survival rate for women with invasive breast cancer is 91%. The average 10-year survival rate for women with invasive breast cancer is 84%. If the cancer is located only in the breast, the 5-year survival rate of women with breast cancer is 99%0.62% of women with breast cancer are diagnosed with this stage. Adolescent and young adult females ages 15 to 39 in the United States are less likely to be diagnosed at an early stage of breast cancer (47%) compared to women older than 65 (68%). This difference may partially be due to delays in screening in younger women. This clearly shows the importance of early diagnosis of breast cancer for a greater survival rate. AI is incorporated in cancer diagnosis as it has varied functions like risk assessment, diagnosis and detection, prognosis and response to therapy. This diversity of application makes AI in cancer detection ideal and useful.[80]

The outcomes of this paper can be verified only when an elaborate experiment that uses both MLP and CNN for testing the same set of data under same test conditions is performed. Other challenges faced when using ANN for diagnosis of breast cancer can be the reliability, as one of the researches showed that the detection and diagnosis accuracy of radiologists is slightly more than that of ANN based results. Also, the input images that need to be used for training have to be diagnosed in advance and that needs to be done by oncologists or doctors. This makes the overall purpose of incorporating ANN futile, but at the same time, the time spent by the doctors examining each further patient drastically reduces, as the can then employ the Network for the same. This method definitely has a greater future scope in terms of releasing the burden of examining thousands of patients on a single doctor. The efficiency of this process also can be improved by various different functions, methods and training. ANN are self-learning systems and overtime they can reduce errors and at the same time this method reduces the time taken in diagnosis and classification. Thus, ANN in breast cancer diagnosis can prove to be the futuristic tool that aids patients and oncologists.

5. Conclusion

The healthcare system is an integral part of the society that ensures that every individual gets effective diagnosis and treatment. It also performs researches to combat new diseases, viruses and other ailments. Health is a crucial factor for deciding the capabilities of any individual and thus, a healthy life is a need for everyone. The field of medical science aids this ubiquitous need of good health. In this technologically advancing, fast paced world, integrating new technology in the field of healthcare has become essential and inevitable. Technology helps in making ailment diagnosis, treatment, medicine prescription, etc more efficient and less time consuming. It also reduces the need of trained work force. Thus, implementing various technologies in healthcare is a crucial step in advancement of medical sciences.

This paper examines various approaches that use ANN to diagnose breast cancer, and compares Multi-Layer Perceptron Neural

Network and Convolutional Neural Network based on their accuracy of diagnosis and breast cancer classification. Convolutional Neural network is explained in terms of architecture and its working. Then various researches that use CNN for breast cancer detection are examined. Then, Multi-Layer Perceptron Neural Networks are explained with its architecture and working, followed by an elaborate examination of various researches that use MLP-NN for breast cancer diagnosis and classification. Convolutional neural network has convolution and pooling layers that make it the better choice for complex image classifications, however, upon comparison from examination of various experiments, CNN shows higher accuracy than MLP in diagnosing and classifying breast cancer cells. Majority of results propose that CNN gives a high accuracy as various layers like convolutional layer, pooling layer, and fully connected layer are incorporated. The numbers of hidden layers need to be minimised and using artificial metaplasticity in MLP can help minimise error. MLP is closely as efficient as CNN, but CNN shows results with higher accuracy. Yet, the most accurate result can be obtained upon elaborate experiment of breast cancer diagnosis and classification using same dataset in both CNN and MLP-NN under similar conditions of testing and training. But, implementing ANN in breast cancer diagnosis and classification is the need of the hour, in order to reduce work load on doctors who each have to perform diagnosis on several patients per day, improve efficiency and also help women diagnose breast cancer themselves safely by extending this technology to make safe and handy mobile applications.

Authors contribution

All the authors make a substantial contribution to this manuscript. MD and MS participated in drafting the manuscript. MD and MS wrote the main manuscript. All the authors discussed the results and implication on the manuscript at all stages.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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