MAMMOGRAM IMAGE CLASSIFICATION USING LOCAL BINARY CONVOLUTIONAL NEURAL NETWORK

[1]HADEEL ABDULMAJEED, [2] MOHAMMAD SHKOUKANI
[1] Department of Computer Science, Applied Science Private University, Amman, Jordan
[2] Prof., Department of Computer Science, Applied Science Private University, Amman, Jordan
E-mail: [1]hadeelaj@yahoo.com, [2] m.shkokani@asu.edu.jo

ABSTRACT

Breast cancer is considered one of the most common cancer in women worldwide, reducing the risk of mortality is by early detection of cancer and providing the appropriate treatment. Working on mammography using machine learning can help detecting and diagnosing cancer.
Convolutional neural network (CNN) is a deep learning technique which is one of the best for detection and classification of abnormalities in medical images. Training CNN models need large datasets so training it on medical datasets from scratch is difficult job because of their small size and the variation of the abnormality shapes in mammogram images, instead it is possible to use pre-trained network because the generic features from such model can be used for new different task like mammogram image dataset that has limited number of images.
This research employed transfer learning by enhancing Local Binary Convolutional Neural Network (LBCNN) model which is deep learning technique to suit our new task and help classifying breast abnormalities in mammogram images by applying it on MIAS database. This includes image preprocessing, feature extraction by optimizing and fine-tuning number of convolutional layers and Finally image classification using new classifier with three classes normal, malignant and benign.
The results proved that the enhanced model successfully predicted the presence of normality or not and its type with accuracy reached 90% in 15 minutes using about 1.2 million parameters which saves memory and time compared to 88.7% accuracy in 28 minutes using about 11.3 million parameters on standard CNN, this lead to conclude that the system capable of detecting and classifying mammogram images saving a lot of parameters.
Keywords*: Mammogram Image, Convolutional Neural Network, Classification, Breast Cancer*

1. INTRODUCTION

Computer Aided detection and diagnosis (CAD) systems are very helpful for detecting and diagnosing cancer in its early stages to increase the chances of successful treatment.
Breast cancer is considered as the most common cancer among other kinds of cancers in women [1], to detect and diagnose lesions in the breast correctly, radiologists face challenges due to the large amount of breast images they have to examine daily and the difficulty of reading the images (i.e., determining the breast masses and correctly diagnosing them). Thus, CAD systems are important as a second opinion in decision making.
There are many medical imaging techniques like MRI (magnetic resonance imaging), ultrasound, X-ray imaging, digital breast tomosynthesis (DBT) and Mammography which is a type of imaging that uses a low dose X-ray system to examine the breast, this system is the most effective radiology technique to detect breast cancer [2].

A mammography exam, called a mammogram, aids in the early detection and diagnosis of breast abnormalities in women, it is imaging using x-rays produce pictures of the inside of the body.
There are different types of mammography include conventional mammography that gives an x-ray film, digital mammography in which the x-ray film is converted automatically into a digital image by using some electronics then transfer them on a computer to be reviewed by the radiologist, last type breast tomosynthesis (3 D image). Computer-aided detection & diagnosing systems (CADe) and (CADx) search digitized mammographic images for abnormal areas that may indicate the presence of cancer. These systems highlight those areas on the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

images, alerting the radiologist of the presence of some findings, many researches have been made to use CADx in the task of diagnosing breast cancer by using classification algorithms to classify malignant or benign lesion based on features extracted from the image data [3].

The traditional methods used for diagnosing lesions in medical images include using hand-crafted features like (shape, size, density ... etc.) of the tumor.

So, employing deep learning using Convolutional Neural Network made it easier as one of the most powerful machine learning tools in computer vision and image classification, this type of neural nets can simplify the image to a set of features and learn high level features directly from the image to give more accurate recognition [1]. CNN needs large amount of data to train it and get accurate results, it’s hard to train CNN from scratch for medical images because of small datasets [3], based on that pre-trained CNN on huge dataset like ImageNet can be used for new task, that’s called transfer learning which can be used by fine-tuning some layers (high level features layers) of the network to calculate feature maps for new types of data [1].

Convolutional neural networks have developed many architectures in the past few years, AlexNet [4], VGG [5], Inception [6] and ResNet [7], [8], However, training these networks end-to-end with fully convolutional is expensive computationally, results in big model size, due to memory usage and disk space, and is prone to over-fitting, under limited data, due to the large number of parameters. To treat these problems, many binary versions of CNNs have been proposed that approximate the dense real-valued weights with binary weights. Binary weights resulting a lot of computational savings when implementing in efficient way.

2. IMAGE PROCESSING

Image processing is a type of a signal processing in which the input is an image, and the output may be an image or features associated with that image. It is a way to perform some operations on an image that has been converted into numerical form, then to be able to get an enhanced image or to extract some information from it [9].

Image processing consists of the following operations:

- Image pre-processing: It refers to operations work on single pixels which perform improvement or enhancement on images to clarify important features in it which can be needed for further processing [9].
- Segmentation: It is one of the important processes in image processing and analysis, it means dividing the image into objects, the level of division depends on the problem and what solution will be suitable for it. The process has to stop when the required object is isolated from other objects in the image [11], [12].
- Feature Selection: It represents the image information in attributes to use them for further processes. These features will be represented in numerical values to describe the region of interest uniquely after isolating the objects by segmentation process [9].
- Classification: It is the labeling of a pixel or a group of pixels based on its grey value, extracted features from images make it easier to label image objects to classes. Before going through this process, the features must be selected carefully in terms of type and quantity to get accurate classification. There are two types of classification supervised and unsupervised; the most used techniques for classification are Support Vector Machine (SVM) and Artificial Neural Network (ANN) [13], [26].

3. MEDICAL IMAGINING

Medical image processing, analysis, and visualization applications enable quantitative analysis and visualization of medical images of several forms such as: PET, MRI, CT, or microscopy. Imaging has become an essential component in many fields of bio-medical research and clinical practice [14].

Medical images are primarily visual in nature; however, visual analysis by human observers is usually associated with limitations caused by inter observer variations and errors due to fatigue, limited experience, and distractions. Computer analysis, if performed with the appropriate care and logic, can potentially add objective strength to the interpretation of the expert [14], [27].

4. ARTIFICIAL NEURAL NETWORKS

ANN is a processing system which is inspired by how the biological nervous system work & processes information. ANNs gather their knowledge by detecting the patterns and relationships in data and learn (or are trained) through experience, not from programming. An

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ANN is formed from hundreds of single nodes called artificial neurons, connected via weighted links called (weights), these connected neurons constitute the neural structure and are organized in layers. The power of neural computations comes from connecting neurons in a network [10].

The simplest structure of ANN Called Perceptron shown in figure 1 which consist of input nodes where the inputs values pass without being changed to go through weighted sum by multiplying inputs (X) with their weights (W) and subtract the bias (b) as presented in the following mathematical equation:

$$Y` = (x_1\, w_1 + x_2 w_2 + \ldots + x_n\, w_n - b) \;\ldots.\; (1)$$

then this summation uses an activation function like the sign function to produce an output [15].

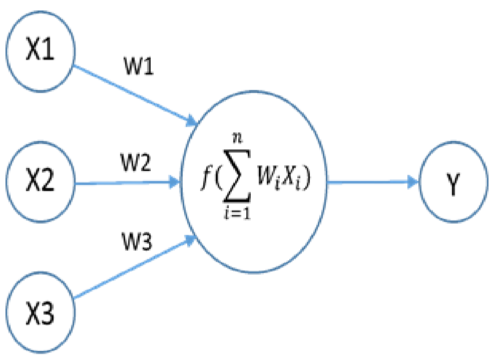

Figure 1: The simplest structure of ANN

5. CONVOLUTIONAL NEURAL NETWORKS

The notable difference between CNN and traditional ANN is that CNN mainly used in pattern recognition algorithms in image processing [11]. The most important features are the simplicity of its structure, weight sharing which reduce the number of used weights and adaptability. This structure makes it easier to deal with images, as the CNN has two jobs in its layers one is for feature extraction and feature map and the other for classification. The last layer will contain loss functions associated with the classes, and all the regular processes developed for traditional ANNs still apply [18].

In a regular neural net, it receives input vector which goes through some hidden layers, each one of these hidden layers is made up of group of neurons where each one is fully connected to all neurons on the previous layer without sharing any connection which lead us to the output layer the last layer. This manner will not go well for a full image, because we will need big number of parameters which is a wasteful [12]. So using CNN will be the solution, it takes advantage of the fact that the input consist of images, the neurons in the layers of CNN arranged in three dimensions: the spatial dimension of an image (height and width) the third on is depth which refers to the third dimension of the activation volume [19],[22], [26].

To build CNN architecture as shown in figure 2, three main types of layers are used they are Convolutional layers, Pooling layer and Fully Connected layer (FC).

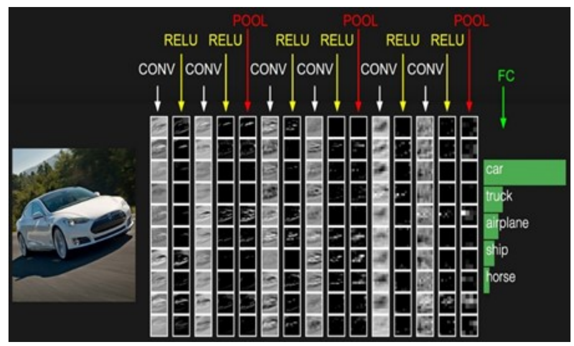

Figure 2: An example of Convolutional Neural Network architecture

6. LOCAL BINARY PATTERN

LBP is an image operator based on the gray level differences between the center and the neighborhood of a pixel. As illustrated in figure 3, the center pixel is compared with its eight neighbors in a 3x3 neighborhood if neighbor value higher than or equal the center value then assign 1 to that position otherwise assign 0; a binary number of 8 digits is obtained from these binary codes in a clockwise direction starting from the top-left one and this binary number is converted to decimal value which is used for labeling. The derived binary numbers are referred to as Local Binary Patterns or LBP codes [21].

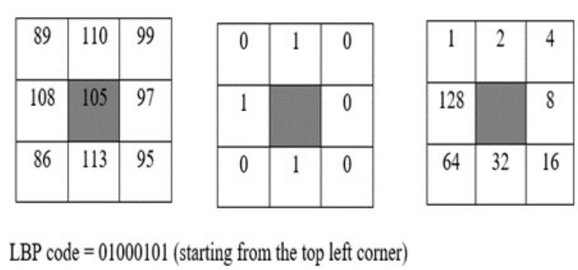

Figure 3: LBP Process

7. BREAST CANCER

The body cells have a cycle of growing and death processes to maintain the mechanism of the body, some of these cells start to grow in unusual way sometimes which create cancerous cells and that may happen in any part of the body then spread out , there are different types of cancer one of them is breast cancer which occurs in women more [13].

The mammographic exam allows detecting and characterizing lesions in the breast. There are many techniques to detect breast lesions, like Ultrasonography and magnetic resonance imaging (MRI), but mammography is the most common choice. There are many types of breast abnormalities: masses, calcification, asymmetry, architectural distortion, adenopathy, but the most common abnormalities that may indicate breast cancer and can be detected by mammogram are masses and calcifications[20], [24], [28].

There are two types of masses: those that are benign means non-cancerous, called (masses), and malignant means cancerous called (tumor) [25].

8. MAMMOGRAM IMAGE

A mammogram is a specific type of breast imaging that uses low-dose x-rays to detect cancer early; there are two views of each breast are recorded; the Craniocaudal (CC) view –head to foot view-, and a Mediolateral Oblique (MLO) view –angled side view as shown in figure 4a and figure 4b, these images are carefully evaluated by radiologist [16], [28].

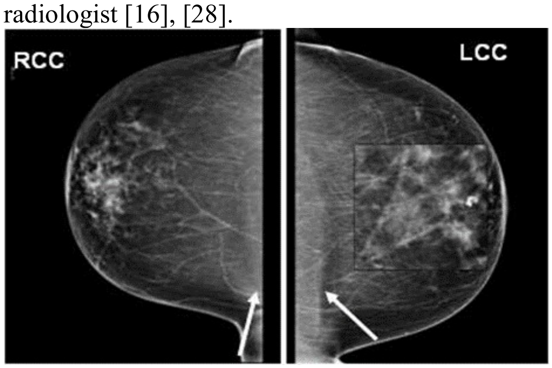

Figure 4a: Mediolateral Oblique (MLO) view

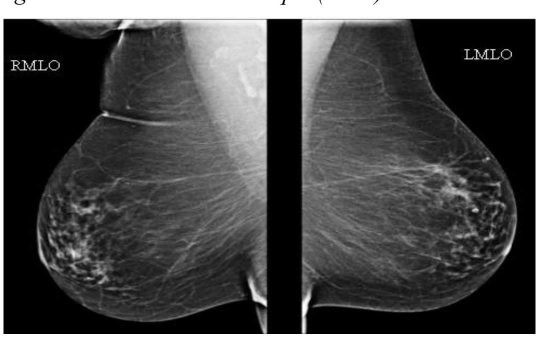

Figure 4b: Craniocaudal (CC) view) view

Mammogram images are difficult to interpret; thus, a pre-processing phase is needed in order to improve the image quality and make the classification results more accurate. The first step involves removing of artifact and unwanted parts in the background of the mammogram. Then, an enhancement process is applied to the digital mammogram. Image enhancement operations can be used to improve the appearance of images, to eliminate noise or error, or to illustrate certain features in an image [17], [23].

9. PROBLEM STATEMENT

Mammogram image is the most important technique to detect breast cancer or any abnormality in the breast, these findings can be diagnosed by the physician either as benign or malignant and can be detected in the first stages by using new technologies to make it easier for the medical staff to take the right decision and protect the patients from going for further investigations like biopsy or other procedures.

Convolutional neural network are being used for feature extracting and classifying all kind of images including medical images, so as local binary pattern which is one of the most effective techniques for feature extraction, so by combining these two techniques new state-of-art Local binary convolutional neural network (LBCNN) have been built to work on natural images, based on that the authors propose an enhancing model and apply it on mammogram images to obtain more accurate results using less parameters and faster processing time.

10. PROPOSED APPROACH

As shown in figure 5, the propose approach consists of the following steps:

- Image preprocessing includes cropping, normalization, augmentation.
- Change the fully connected layers that includes the classifier which will be with our new classes (Normal, Benign, Malignant), a SoftMax function will be used.
- Freeze the earlier layers which mean keep their weights and stop the gradient descent from updating them because they have the general features and we don't want to disrupt them.
- Divide the convolutional layers into five blocks each block contains 10 layers.
- Fine tune the top block of convolutional layers by allowing backpropagation to these layers because

they will produce more specific features of the new dataset, convolutional layers works like feature extractor these layers do their job without interfering from us by adjusting the weights of the filters to produce the right features needed based on the datasets used in the training process.

- Setting parameters before Starting the training, learning rate, the number of epochs, the number of iterations depends on the batch size and the size of dataset, images in the dataset will be divided into 75% for training and 25% for evaluation and testing images.

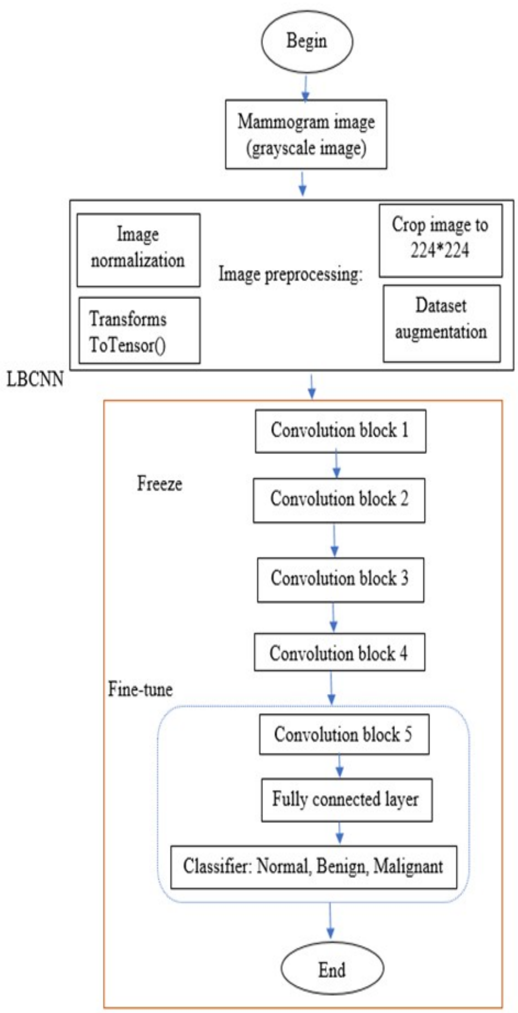

Figure 5: Flow Chart of the Proposed Solution

11. PROPOSED ALGORITHM IMPLEMENTATION

The authors used mini-MIAS database (Mammographic Images Analysis Society) which contain 322 mammogram images representing left and right breast of 161 patients, 133 abnormal that means any kind of abnormality (Benign or Malignant) and 189 of normal, each image of size 1024*1024 and in portable gray map (.pgm) format, which is a gray scale image, each image contain marked positions defined by the radiologist determining the abnormality in addition to the coordinates (x, y) of the center of abnormality, these images are classified into seven classes: Well-defined/circumscribed mass, speculated mass, calcification, Architectural distortion, Asymmetry, normal, miscellaneous (other, ill-defined masses).

The authors used laptop with NVIDIA GTX 1060 which is 6.0 compute capability, 16 GB of RAM in addition to the hardware requirements it needs to install the following dependencies: NVIDIA CUDA, NVIDIA cuDNN, based on this the authors used Linux Ubuntu 18.04 then installed CUDA 10.1 and the mentioned dependencies then installed Torch and cuDNN bindings.

11.1 Preprocessing MIAS Dataset:

The author split the dataset into three folders:

- Train folder: contains 75% of the images that is 240 images which in turn divided into three folders (three classes) named Normal, Benign and Malignant.
- validation folder: contains 15% of the dataset that's (50 images) and its subfolders are arranged in the same manner as in the train folder, using validation sets is for control the hyper-parameters of a model it is like a fake test set to evaluate the performance of the model and tune the hyper-parameters.
- Test folder: contains 10% of the images these images are not labeled because they will test the performance of the model, 32 images.

11.2 Image Preprocessing:

According to the proposed algorithm the following steps for image preprocessing:

- **Resize:** the images to size 224 * 224 by cropping the black edges and the pictorial muscle, using the given coordinates of the lesion center to form a box surrounding the abnormality in the images.
- **Transforms To Tensor():** converts the image into numbers, by converting the pixels of each image into the brightness of their color, from 0 to 255.
- **Normalize:** the images using dataset mean and standard deviation by compute the mean, and the

standard deviation of the images' pixels then subtract the mean from each pixel then divide the results by the standard deviation, This process is important to deal with brightness levels because of using different types of scanners.

- **Data augmentation:** this process aims to artificially increase the number of training images seen by the model, by applying random transformations to the images, the transformation used here are horizontal flip and random rotation of each image in the dataset because a lesion should be recognized in any orientation. In addition, it reduces overfitting and lead to more efficient work for the network because 322 images in this dataset considered small compared the data sets of natural images.

11.3 Transfer Learning Steps:

- In the beginning we load in our pre-trained model that trained on a large dataset.
- we kept the original network architecture up till the fully connected layers. The original fully connected layers were built for the used datasets with different number of class for the categories of each dataset used, so we changed the class layer to be equal to our number of classes i.e. three classes (normal, Benign, Malignant).
- Then, we used the model as fixed feature extractors and the log SoftMax function on top as a classifier, by freezing all the weights in the lower (convolutional) layers and unfreezing the fully-connected layers by back propagating their weights, the size of FC layer is 512 neurons using ReLU function and the last one which is the class score layer has 3 classes then go forward with the training, this step before fine-tuning Convolutional layers improves the performance of the network.
- The next step is fine tuning some last convolutional layers, the network has 50 layers so we divided the convolutional layers into blocks, the last block contains 10 layers, the weights in these layers will be adjusted to the new data sets.

The reason behind keeping the first convolutional layers of a CNN intact because they learn generic features and can perform more like edge detectors, which should be useful to another tasks, but the following layers become gradually more specific to the details of the classes contained in the dataset.

11.4 Parameter Settings:

The batch size is set to 5, the number of epochs is 60. The primary learning rate is 10^{-4} which is less than the default 10^{-3} because high learning rate for fine tuning may cause undesirable behavior of divergent, to deal with this problem a common method have been used, it's "step decay" where the learning rate is reduced after every few epochs by multiplying it with a factor. Learning rate decay is how to slowly reduce learning rate. We used the same filter size 3*3 for the fixed binary filters, other parameters like pooling size, strides, batch normalization, activation function are set as default values.

12. RESULT AND DISCUSSION

The authors implemented the algorithm twice for fair comparison by training on the LBCNN model first and training on traditional CNN with the same structure using learnable weights (not fixed) for the 3*3 filters and 1*1 filter.

12.1 LBCNN Experiment:

The authors used the pre trained LBCNN model as feature extractor, reset the classifier by setting it to (`th main.lua -resetClassifier true -nClasses 3 -retrain pretrained/resnet-binary-felix -nEpochs 20 -data [dataset path] -save [data path] -batchSize 5 sparsity 0.5`. Train the FC layers for 20 epochs by setting (`accGradParameters` to `true`) in these layers only, while convolutional layers are frozen by setting the Grad parameters to false we obtained 83% of accuracy. The accuracy will be improved when the fine tune process is applied.

Fine-tuned the last 10 convolutional layers by fixing the weights in earlier layers then allow the back propagation of the weights for the 10 layers and the FC layers; That means allow for updating their weights, by iterating the training for 60 epochs this time So we obtained more accurate results 90.22% of overall accuracy, this process took 15 minutes to finish, using 1,247,849 parameters and this is about 9 times less than the parameters used in the next experiment.

Figure 6 shows a plot of accuracy for the performance of LBCNN on classifying mammogram image dataset which means it is a successful experiment to obtain such accuracy by training small with different type of images dataset.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

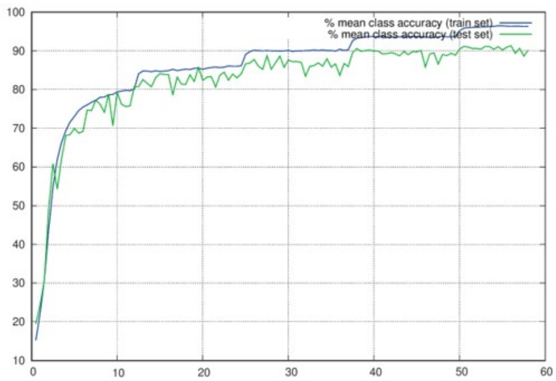

Figure 6: Accuracy plot over the epochs for LBCNN on MIAS Dataset

It's noted how the accuracy of training and testing sets for LBCNN model (first experiment) is gradually improving as shown in table 1

Table 1: Implementation results for LBCNN model

% mean class accuracy (train set)	% mean class accuracy (test set)
1.5222e+01	1.9450e+01
2.2322e+01	2.4440e+01
3.1052e+01	3.0940e+01
4.3966e+01	4.9280e+01
5.4852e+01	6.0840e+01
6.1907e+01	5.4280e+01
6.6334e+01	6.2080e+01
6.9365e+01	6.8140e+01
7.1647e+01	6.8370e+01
7.3029e+01	6.9950e+01
7.4569e+01	6.8770e+01
7.5469e+01	6.9160e+01
. .	
8.0194e+01	8.0760e+01
8.4101e+01	8.0780e+01
8.4800e+01	8.2580e+01
8.4772e+01	8.1650e+01
8.4601e+01	8.0710e+01
. .	
9.6214e+01	9.1160e+01
9.6308e+01	9.1090e+01
9.6308e+01	9.0400e+01
9.6496e+01	9.1090e+01
9.6466e+01	9.0260e+01
9.6372e+01	9.0940e+01
9.6356e+01	9.1330e+01
9.6374e+01	8.9360e+01
9.6372e+01	9.0660e+01
9.6278e+01	8.8620e+01
9.6328e+01	9.0220e+01

Table 2 is the confusion matrix that represents the response of the LBCNN after fine tuning and applying it on MIAS database as a feature extractor and classifier, it shows the result of accuracy for each class.

Table 2: Confusion matrix for MIAS dataset prediction using the LBCNN model

Total Accuracy 90.22 %	Benign	Malignant	Normal
Benign	87.77	8.53	3.70
malignant	2.81	92.53	4.66
normal	7.21	2.43	90.36

12.2 Baseline CNN Experiment:

As mentioned before there is a baseline CNN architecture similar to LBCNN, that is 3*3 filter With lendable weights and 1*1 filter, to compare the result of our model to it; so we used the Same exact procedure for the pre trained CNN model by resetting the classifier then train the model for 20 epochs, we obtained 82.4% Of accuracy, then fine-tuned the last 10 convolutional layers by allowing to back propagate the weights for these layers and the FC layers, freeze the earlier layers; by that the results were about 88.72% as shown in figure 7, this process took around 28 minutes to finish which is about twice the time used in LBCNN , using 11,320,849 parameters and this number is much more than the number of parameters in the LBCNN experiments.

Journal of Theoretical and Applied Information Technology
31st January 2022. Vol.100. No 2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

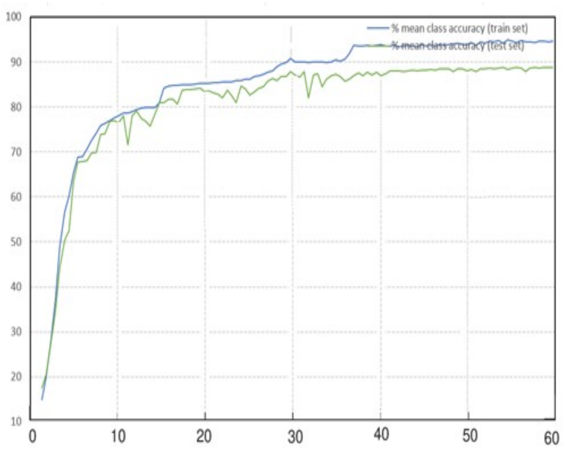

Figure 7: Accuracy plot over the epochs for CNN on MIAS Dataset

As shown in table 3 the results of baseline CNN experiment and how the accuracy of the training sets and test sets gradually improving.

Table 3: Implementation results for Baseline CNN model

% mean class accuracy (train set)	% mean class accuracy (test set)
1.4832e+01	1.7543e+01
1.9884e+01	2.0644e+01
2.8340e+01	2.7855e+01
3.7205e+01	3.4622e+01
4.8942e+01	5.4430e+01
5.6623e+01	5.0344e+01
6.0204e+01	5.2462e+01
6.5334e+01	6.3853e+01
6.8822e+01	6.7664e+01
6.8960e+01	6.7842e+01
7.0663e+01	6.8044e+01
7.2532e+01	6.9755e+01
. .	
8.8951e+01	8.5822e+01
8.9475e+01	8.6730e+01
8.9881e+01	8.6813e+01
9.0733e+01	8.7921e+01
8.9988e+01	8.7011e+01
. .	
9.4963e+01	8.8297e+01
9.4607e+01	8.8607e+01
9.4286e+01	8.8700e+01
9.4835e+01	8.8689e+01
9.4378e+01	8.7801e+01
9.4432e+01	8.8676e+01
9.4353e+01	8.8742e+01
9.4562e+01	8.8691e+01
9.4643e+01	8.8706e+01
9.4425e+01	8.8738e+01
9.4635e+01	8.8726e+01

Table 4 is the confusion matrix that represents the response of the baseline CNN after fine tuning and applying it on MIAS database as a feature extractor and classifier, it shows the result of accuracy for each class.

Table 4: Confusion matrix for MIAS dataset prediction using the Baseline CNN model

Total Accuracy 88.72 %	Benign	Malignant	Normal
Benign	86.57	9.07	5.36
malignant	6.11	91.16	2.73
normal	7.35	4.22	88.43

Finally, the researchers used transfer learning technique trying different strategies on two network architectures using mammogram images (MIAS dataset). For each experiment (LBCNN and baseline CNN) two strategies have been used.

The first one by resetting the classifier and the fully connected layer using the model as feature extractor which gave of accuracy 83% for the first experiment (LBCNN) and 82.4% for the second experiment (Baseline CNN), this approach helped improving the performance of the model when fine tuning strategy were used.

In fine tuning step most of the convolutional layers where frozen and only the last block (10 convolutional layers) could back propagate the weights and that gave good accuracy results 90% in 15 minutes with fewer number of parameters reaches to 1,247,641 parameters.

While the second model baseline CNN achieved accuracy results 88% in 28 minutes using 11,230,849 number of parameters.

Transfer learning and fine tuning allow using trained weights of different network models with less effort by keeping earlier layers unchanged as they contain generic features that are usable in almost any type of images, this is very helpful with small datasets, because training convolutional neural network from scratch require large datasets due to overfitting concerns. This technique help introducing systems that can classify normal from abnormal mammogram images and work as a second opinion to help medical staff.

13. COMPARISON BETWEEN THE PROPOSED MODEL AND OTHER WORKS

Many researches were conducted on feature extraction and classification of mammogram images using different techniques. Some important works were developed using CNN, such as:

Paper [29] presents an application of deep Convolutional Neural Networks (CNN) for the detection and diagnosis of breast cancer using a CNN for feature extraction and SVM for classification. The accuracy results for the proposed approach they compared between mammogram images without augmentation and images after augmentation yield very low accuracy which was 64.52%.

The authors in Paper [30] used a new technique to classify breast cancer using convolutional neural network, the final accuracy results they have reached 85%.

The authors [31] trained CNN from scratch to detect and classify breast cancer using MIAS mammogram dataset, according to their approach the obtained accuracy was 65%.

In paper [32] they propose a computer aided diagnose system based on ROI-based convolution neural network. The overall accuracy is 85.52% obtained by applying this model on DDSM database.

If we compare our proposed model result which is 90% with the related works' result, we can find that we obtained better results, in addition to another advantage which is reducing the number of parameters about nine times than original model.

14. CONCLUSION AND FUTURE WORK

This paper proposed a model which aims to reduce the number of parameters to become 1.2 million parameters instead of 11.3 million parameters which is about 9 times less than a regular CNN model. It also reduces memory usage because of low computational complexity. The proposed model was better than CNN model in accuracy since accuracy becomes 90% instead of 88%. Based on that the authors proved that the proposed model can be used for medical images successfully giving an accurate result.

The authors also proved that transfer learning is an efficient method to train small datasets instead of starting from scratch which prevents overfitting, reduces the time of training and gives better performance.

As future work the proposed algorithm can be enhanced by using different binary filter sizes, different sparsity distribution technique, and fine tuning more convolutional layers.

15. ACKNOWLEDGMENTS

The authors are grateful to the Applied Science Private University, Amman, Jordan, for the full financial support granted to this research.

REFERENCES:

[1] Xiaofei Zhang, Yi Zhang, Erik Y. Han, Nathan Jacobs, Qiong Han, Xiaoqin Wang, Jinze Liu, Zhang and Yi, "Whole Mammogram Image Classification With Convolutional Neural Network," in *2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, Kansas City, MO, 2017.

[2] Jelena Bozek, Mario Mustra, Kresimir Delac and Mislav Grgic, "A Survey of Image Processing Algorithms in Digital Mammography," in *Recent Advances in Multimedia Signal Processing and Communications*, Verlag Berlin Heildeberg, Springer, 2009, pp. 631-657.

[3] Benjamin Q. Huynh, Hui Li and Maryellen L. Giger, "Digital mammographic tumor classification using transfer learning from deep convolutional neural networks," *Journal of Medical Imaging - spie digital library,* vol. 3, no. 3, 2016.

[4] A. Krizhevsky, I. Sutskever and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," *Advances in Neural Information Processing Systems (NIPS),* pp. 1097-1105, 2012.

[5] Karen Simonyan and Andrew Zisserman, "Very Deep Convolutional Networks for Large-scale Image Recognition," in *International Conference on Learning Representations (ICLR)*, 2015.

[6] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed and D. Anguelov, "Going Deeper with Convolutions," *IEEE Conference on Computer*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Vision and Pattern Recognition (CVPR), pp. 1-9, 2015.

[7] K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition.," *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR),* p. 770–778, 2016.

[8] K. He, X. Zhang, S. Ren and J. Sun, "Identity Mappings in Deep Residual Networks," *European Conference on Computer Vision (ECCV),* p. 630–645, 2016.

[9] Rafael C. Gonzalez and Richard E. Woods, Digital Images Processing 2nd edition, Prentice Hall, 2002.

[10] Gholamerza Anbarjafari, University of Tartu, "Digital Image Processing," SISU@UT, 2014. [Online]. Available: https://sisu.ut.ee/imageprocessing/book/1. [Accessed 26 february 2019].

[11] B. Chitradevi and P.Srimathi, "An Overview on Image Processing Techniques," *International Journal of Innovative Research in Computer and Communication Engineering,* vol. 2, no. 11, 2014.

[12] R.Yogamangalam and B.Karthikeyan, "Segmentation Techniques Comparison in Image Processing," *International Journal of Engineering and Technology (IJET),* vol. 3, no. 1, 2013.

[13] Malgorzata and Verőné Wojtaszek, Data acquisition and integration 6., 6 Remote Sensing, Budapest: Nyugat-magyarországi Egyetem, 2010.

[14] Debashis Ganguly, Srabonti Chakraborty, Maricel Balitanas and Tai-hoon Kim, "Medical Imaging: A Review," in *Security-Enriched Urban Computing and Smart Grid*, Daejeon, Springer, pp. 504-516, 2010.

[15] S Agatonovic-Kustrin and R Beresford, "Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research," *Journal of Pharmaceutical and Biomedical Analysis,* vol. 22, no. 5, pp. 717-727, 2000.

[16] Neeraj Dhungel and Gustavo CarneiroAndrew P. Bradley, "The Automated Learning of Deep Features for Breast Mass Classification from Mammograms," in *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2016*, Athens, Greece, Springer, pp. 106-114, 2016.

[17] Pengcheng Xi, Chang Shu and Rafik Goubran, "Abnormality detection in mammography using deep convolutional neural network," in *2018 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*, Rome, Italy, 2018.

[18] Tianyi Liu, Shuangsang Fang, Yuehui Zhao, Peng Wang and Jun Zhang, "Implementation of Training Convolutional Neural Networks," arXiv.org - Cornell University, 2015.

[19] Keiron O'Shea and Ryan Nash, "An Introduction to Convolutional Neural Networks," arXiv.org - Cornell University, 2015.

[20] Saira Charan, Muhammad Jaleed Khan and Khurram Khurshid, "breast cancer detection in mammograms using convolutional neural network," in *2018 International Conference on Computing, Mathematics and Engineering Technologies (iCoMET)*, Sukkur, Pakistan, 2018.

[21] D. Huang, C. Shan, M. Ardabilian, Y. Wang and L. Chen, "Local Binary Patterns and Its Application to Facial Image Analysis: A Survey," *IEEE Transactions on Systems Man and Cybernetics Part C (Applications and Reviews),* vol. 41, no. 6, pp. 765-781, 2011.

[22] Yamashita, R., Nishio, M., Do, R.K.G. *et al.* Convolutional neural networks: an overview and application in radiology. *Insights Imaging* **9,** 611–629 (2018). https://doi.org/10.1007/s13244-018-0639-9

[23] Xuejiao Tang, Liuhua Zhang, Wenbin Zhang, Zhen Liu, Mingli Zhang , Enza Messina, Ji Zhang, " Using Machine Learning to Automate Mammogram Images Analysis", Electrical Engineering and Systems Sciences, arXiv.org, vol. 19, no. 7, 2020.

[24] Kong, Abdullah-Al Nahid and Yinan, "Involvement of Machine Learning for Breast Cancer Image Classification: A Survey," *Computational and Mathematical Methods in Medicine,* vol. 2017, no. Article ID 3781951, p. 29, 2017.

[25] Rita Filipa dos Santos Teixeira and Prof. João Manuel R. S. Tavares, *M. Sc. Thesis in AUTOMATIC ANALYSIS OF MAMMOGRAPHY IMAGES: CLASSIFICATION OF BREAST DENSITY,* Porto: Faculdade de Engenharia da Universidade do Porto, 2013.

[26] M Aljanabi, M Shkoukani, M Hijjawi, “Ground-level ozone prediction using machine learning techniques: A case study in Amman, Jordan”, *International Journal of Automation and Computing*, Vol. 17, pp. 667-677, 2020.

[27] A. Casamitjana, M. Lorenzi, S. Ferraris, L. Peter, M. Modat, A. Stevens, B. Fischl, T. Vercauteren, J. Iglesias, Robust joint

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

registration of multiple stains and MRI for multimodal 3D histology reconstruction: Application to the Allen human brain atlas, Medical Image Analysis, Vol. 75, 2022.

[28] E. Michael, H. Ma, H. Li, F. Kulwa, J. Li, "Breast Cancer Segmentation Methods: Current Status and Future Potentials", *BioMed Research International*, vol. 2021, Article ID 9962109, 2021.

[29] Jose Gallego-Posada, Diego Montoya-Zapata and O. L. Quintero-Montoya, Detection and Diagnosis of Breast Tumors using Deep Convolutional Neural Networks, Medellin: Semantic Scholar, 2016.

[30] Y. J. Tan, K. S. Sim and F. F. Ting, "Breast cancer detection using convolutional Neural networks for mammogram imaging system," in 2017 International Conference on Robotics, Automation and Sciences (ICORAS), Melaka, Malaysia, 2017.

[31] Saira Charan, Muhammad Jaleed Khan and Khurram Khurshid, "breast cancer detection in mammograms using convolutional neural network," in 2018 International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), Sukkur, Pakistan, 2018.

[32] M. A. Al-masni, M. A. Al-antari, J. M. Park, G. Gi, T. Y. Kim, P. Rivera, E. Valarezo and S.-M. Han, "Detection and Classification of the Breast Abnormalities in Digital Mammograms via Regional Convolutional Neural Network," in 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Seogwipo, South Korea, 2017.