Classification of Mammograms using Attention Learning for Localization of Malignancy

Manaswini Nagaraj, Vignesh Prabhakar, Sailaja Thota

Abstract*: *Mammography is a specialized medical imaging that uses a low-dose x-ray system to examine the breasts. A mammogram is a mammography exam report that helps in the detection and diagnosis of breast diseases in women at an early stage. This project proposes to classify mammography breast scans into their respective classes and uses attention learning to localize the specific pixels of malignancy using a heat map overlay. The attention learning model is a standard encoder-decoder circuit wherein convolutional neural networks perform the encoding and recurrent neural networks perform the decoding. Convolutional neural networks enable feature extraction from the mammography scans which is thereafter fed into a recurrent neural network that focuses on the region of malignancy based on the weights assigned to the extracted features over a series of iterations during which the weights are continuously adjusted owing to the feedback received from the previous iteration or epoch. Mammography images are equalized, enhanced and augmented before extracting the features and assigning weights to them as a part of the data preprocessing procedures. This procedure would essentially help in tumor localization in case of breast cancers.

Index Terms*: *Attention learning, Convolutional neural networks, Encoder-Decoder, Recurrent neural networks.

I. INTRODUCTION

Mammography is used for breast examination in order to diagnose the presence of breast cancer. There are several classes of breasts in mammography scans. The standard collection of open source medical imaging, mammography datasets contain seven different classes of breasts in mammography. Tumors associated with any of these classes could be either malignant, benign or absent. In order to locate the region of tumor in the mammography scan we need to extract the features from a collection of closely associated image pixels and assign initial weights to them which can be updated upon feedback through backpropagation in order to provide attention to few selective features which are representative of the malignancy. This process is achieved through an encoder-decoder circuit which is an integration of a convolutional neural network and a recurrent neural network.

Revised Manuscript Received on April 24, 2019

Manaswini Nagaraj, Computer Science Engineering, REVA University, Bangalore, India.

Vignesh Prabhakar, Computer Science Engineering, SRM Institute of Science and Technology, Chennai, India.

Sailaja Thota, Computer Science Engineering, REVA University, Bangalore, India.

Once the classifier has been built and trained on the training data of mammography images, it can be deployed to predict the classes of the mammography images in the test data. Visualization of the malignant region can be emphasized using overlays. Performance metrics & classification report ought to be generated to monitor the efficacy of our classifier's performance on the test data.

Thereafter the model could be utilized as a diagnosis tool in order to describe the mammography report for a given user.

II. LITERATURE SURVEY

The literature survey conveys the proposed research work on measures adopted in order to carry out mammography scans classification for the diagnosis of malignancy associated with each scan.

Classification based on multiple association rule (CMAR): This method proposed a neural network classifier. Nodes in input layer are representative of one characteristic from each rule. The number of input nodes were equivalent to the number of characteristics, number of hidden nodes were equivalent to the number of rules and number of output nodes were equivalent to the number of mammography classes. Backpropagation is used for learning the network model with a 10-fold cross validation and sigmoid activation function. The sensitivity and specificity are calculated to plot the ROC curve in order to measure the performance of the classifier. Classifier based on multiple association rule with neural network yields an accuracy of 84.5% albeit in a smaller dataset with huge bias in the training instances available under each class [1].

Two-dimensional discrete wavelet transform classifier: Feature vectors are generated by grey level co-occurrence matrix to all detailed co-efficients from 2D- discrete wavelet transformation of the region of malignancy. Derivation of relevant features are done through f-test and t-test of random sampling. Area under receiver operating characteristic (ROC) curve is better. Accuracy is abnormally high due to absence of measures to avoid overfitting such as a dropout. Assignment of weights to the features representing the region of malignancy or interest & adjustment of these weights from the attained feedback is absent thereby denying the process of attention [2].

Adaboost based multiple support vector machines for recursive feature elimination (SVM-RFE) for mammogram classification: it is a wrapper variant feature selection procedure. Ranking of features is done by the SVM-RFE by calculating information gain during iterative backward feature elimination. In each iteration the SVM-RFE sorts features in working set in order of distinctions between the objective functions and removes the feature with minimal distinction. Ensemble method is used to combine the SVM-RFE with the boosting approach to carry out replication of original dataset by random resampling to gain a higher improvement of this ensemble each replicate is different from one another to attain maximal classification accuracy. Ensemble method of integrating multiple SVM-RFE with AdaBoost performs great on the classification paradigm but a simpler visualization of the region of interest on the scans in an unbiased mammography dataset is missing [3].

Classification of normal and abnormal patterns for diagnosis of breast cancer in digital mammograms in the DDSM dataset performs feature extraction using a grey level co-occurrence matrix (GLCM). This is followed by offering the GLCM as an input to the neural network in order to train the classifier and test its performance on the test data allocated from the DDSM dataset. It produced a classification output between one of the two classes (cancer positive and normalcy). The classification report had a large number of true positives but an even larger number of false negatives which indicated that the classifier had a lot of misclassifications of cancer positive scans as normal ones. Thereby the classifier results were not reliable [4].

Breast imaging report & data systems (BIRADS) classification in mammography: This procedure describes features in the mammography scans such as mass, shape, densities, architectural distortions & location of lesions in order to report the breast abnormalities such as fatty breasts, fibrograndular breasts, heterogeneously & homogeneously dense breasts etc. It also includes lexicon & descriptive representations of the anomalies as well as recommendations & annotations based on specific mammographic cases. Although the feature selection and information availability are variant as well as exhaustive; it does not offer mundane visualization which would be more comprehensive to the patients without much intervention from the radiologists [5].

III. PROPOSED METHOD

The objective of the paper is to propose a methodology which could classify the mammography scans into one of the given classes and localize the malignancy region on the test samples using attention learning model.

A. Technical Specification

The technical aspects of the proposed idea would include:

- Tesla K80 GPU
- 4 GB of exclusive allocation of RAM.
- Open source datasets for mammography.
- Cloud services that offer python 3 notebook with all necessary packages pre-installed and ready to be imported.

B. Dataset

The emerging innovations in mammography classification require datasets with a wide range of images belonging to various classes of breasts. These datasets can be generated by aggregation of the. pgm scan images inside a particular folder which is followed by compression of the same in order to make it easily available for utilization.

1) MIAS Mammography Dataset: The mammographic image analysis society is an open source medical imaging dataset that contains 322 unique scan images at a resolution of 50 microns in the .pgm format (portable grey map) [6].

2) DDSM Mammography Dataset: The digital database for screening mammography is the largest available open source mammography dataset that contains 2620 scan instances along with the respective pathological description of each scan [7].

IV. METHODOLOGY

A. Description of the sequence of activities.

The sequence of activities for generating and training the classifier in order to accurately classify the test mammography scan images followed by application of attention learning mechanism for malignancy localization in the same have been listed below:

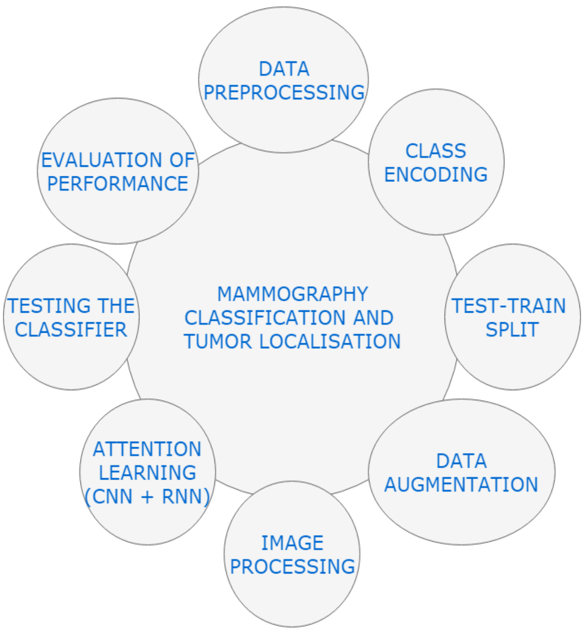

Figure 1. Module-wise implementation of the attention learning model for mammography classification

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

B. Data Preprocessing

	BG	CLASS	RADIUS	REFNUM	SEVERITY	X	Y	path	scan
167	D	ARCH	42.0	mdb165	B	537.0	490.0	mdb165.pgm	tiffs/mdb165.tif
110	D	ASYM	51.0	mdb110	M	190.0	427.0	mdb110.pgm	tiffs/mdb110.tif
13	G	MISC	31.0	mdb013	B	667.0	365.0	mdb013.pgm	tiffs/mdb013.tif
163	D	NORM	NaN	mdb161	nan	NaN	NaN	mdb161.pgm	tiffs/mdb161.tif
96	F	NORM	NaN	mdb096	nan	NaN	NaN	mdb096.pgm	tiffs/mdb096.tif

Figure 2. The preprocessed dataset and the associated attributes after the conversion of the pgm images to tiff from the assigned path.

The mammography scans are available in the mammographic image analysis society (MIAS) dataset in portable grey map format (.pgm) which is thereafter converted to its equivalent tagged image file format (.tiff) using the unique path assigned to each portable grey map scan images for facilitation of the processing. This step in the procedure is performed in order to ease the processing of images which is relatively complex in the case of a portable grey map format. These tagged image file format instances are saved as a column in the dataset. The various attributes of the preprocessed dataset are analyzed and understood.

C. Class Encoding

The various classes of the mammography scans are understood and a unique class identity number is allocated to each one of them. Thereafter label encoding is performed on the dataset. Application of label encoding furnishes an additional column in the preprocessed dataset called the class identity number which contains numbers from 1 to 7 representing the class of each mammography scan. In addition to this a class vector attribute is added to the dataset and each entry here contains a vector of six 0s that represents the absence of a particular class and one 1 that represents the presence of a particular class. The index positions of the class vector correspond to the class identity numbers.

scan	CLASS_ID	CLASS_VEC
tiffs/mdb014.tif	5	[0.0, 0.0, 0.0, 0.0, 0.0, 1.0, 0.0]

Figure 3. Additional attributes added to the preprocessed dataset after performing label encoding of the mammography classes.

D. Test Train Split

```
train 247 validation 83
```

Figure 4. Number of instances available for training vs the number of instances available for testing after performing the 75-25 train-test split.

Thereafter the testing dataset and training dataset split is performed by allocating 25% of the dataset for testing purposes and 75 % of the dataset for training our classifier. This is done in order to ensure maximum availability of data for training which in turn would yield an accurate model. Before carrying out the split, randomization of the entire dataset is necessary

Histograms comparing the number of training image instances for each class ID is plotted in order to observe the number of training instances available under each mammography class prior to augmentation.

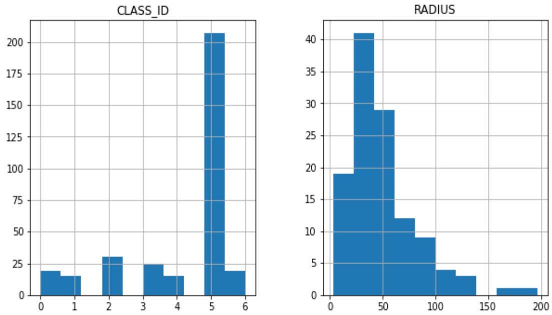

Figure 5. Number of instances available for training with respect to each class identity number prior to augmentation.

E. Data Augmentation

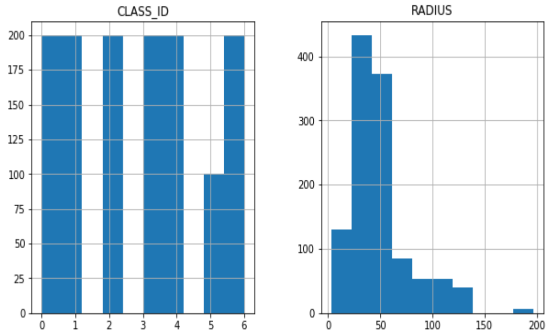

Figure 6. Number of instances available for training with respect to each class identity number post data augmentation.

After performing the split; data augmentation is performed on the training dataset to increment the number of images available for training in order to avoid any inherent bias in the classification of the mammogram scans due to potential scarcity in training images under one or more classes.

Post data augmentation, the histograms comparing the number of training image instances for each class ID is plotted again and similar heights of the bars can be observed in the histogram which indicates the elimination of inherent bias in the availability of training instances for each mammography class.

```
New Data Size: 1300 Old Size: 247
```


Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Figure 7. Number of instances available for training after data augmentation while maintaining the 75-25 train-test split.

F. Image Processing to Remove Noise & Reduce Loss of Information

Once the data is ready for processing, the images are all normalized and shaped into similar aspect of 196X196 pixels to eliminate any noise and loss of information during processing. These normalized images are then processed in batches of 32, 256 and 1024 and re-inserted into training and testing generation data frames. Once the reinserting process is complete the processed images from the training generation data frames are plotted to ensure the successful completion of normalization and reinsertion process.

G. Neural Network architecture And Technical Details

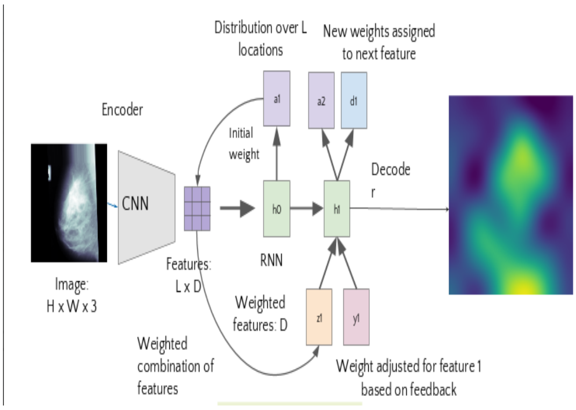

Figure 8. The neural network architecture utilized to train the classifier

The mammography scan image is resized and transformed to the input format (224 X 224 X 3) required for the VGG16 convolutional neural network. This convolutional neural network has 16 hidden layers with very small 3 x 3 convolutional filters and it assigns the probability of belongingness for the input image with respect to each class based on the extracted features. The class corresponding to the maximal probability of belongingness is chosen as the class for the given mammography scan image. After the classification paradigm has been resolved, the extracted feature matrix L x D (D weighted features distributed over L locations) corresponding to that particular class is passed as input to a recurrent neural network architecture. This recurrent neural network has an input layer that considers the extracted features (xi) in the feature matrix one after the another and assigns initial weights to these features (wi). The weighted sum is calculated using the given formula:

$$\sum_{i=1}^{m}(w_i x_i) + bias$$

The calculated weighted sum is updated in the (L x D) feature matrix for each feature and the updated feature matrix is used by the next layer in the RNN to calculate the weighted sum again in order to update the feature matrix once again as done previously. The same procedure is repeated throughout all the 6 hidden layers in our RNN architecture. At the output layer, the expected malignancy feature values are compared with the calculated feature values in the final updated feature matrix. The squared difference between the expected feature value and the calculated feature value is backpropagated as error from the output layer to the hidden layers and then on to the input layer. New initial weights are assigned once again to the features based on the backpropagated error values and the entire process is repeated for a total of 10 epochs. By the end of the 10th epoch, the malignancy features are well learnt and the attention map is applied over the pixels representing the same.

H. Malignancy Localization Using Attention Learning Model

Fine Tuned Convolutional Neural Network (CNN) For Feature Extraction (Encoder-Circuit):

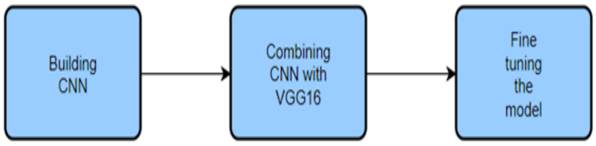

Figure 9. Process of fine tuning a convolutional neural network using the VGG16 (ImageNet).

A fine-tuned CNN ImageNet (VGG16) is utilized to perform the mammography classification to generate the labels for the test dataset scans. In fine-tuned CNN models, the weights of the final layers are readily available due to the pretrained nature of the model and it is merely integrated with the weights of the other layers which are computed by our model.

This reduces the processing time and the computational resources in the case of a massive availability of data. The VGG16 net utilized by our model is a visual geometric group with 16 hidden layers.

Recurrent Neural Network for Assigning Weights to The Extracted Malignancy Feature (Decoder-Circuit):

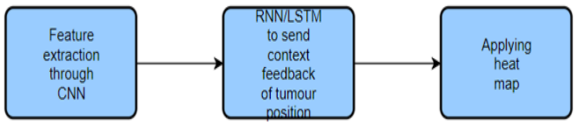

Figure 10. Integration of a CNN (encoder circuit) with an RNN (decoder circuit) to achieve attention learning model.

An RNN/LSTM is utilized to identify the feature to be given attention in the mammography scan by assignment & modification of the weights to the extracted malignancy feature by the RNN through backpropagation over the several iterations/epochs of training. Consequently, over the course of iterations; pronounced retention of malignancy context is achieved. This feature which receives the attention is our malignancy position.

V. TESTING OUR ATTENTION MODEL CLASSIFIER

To represent the region of malignancy in the mammography scan images we utilize a Viridis overlay(heatmap) over the image representing the predicted malignancy class. Thereafter the actual mammography class is compared with the predicted mammography class and accuracy of our model is calculated in order to evaluate the effectiveness of the training and efficacy of the performance of the model on the test data.

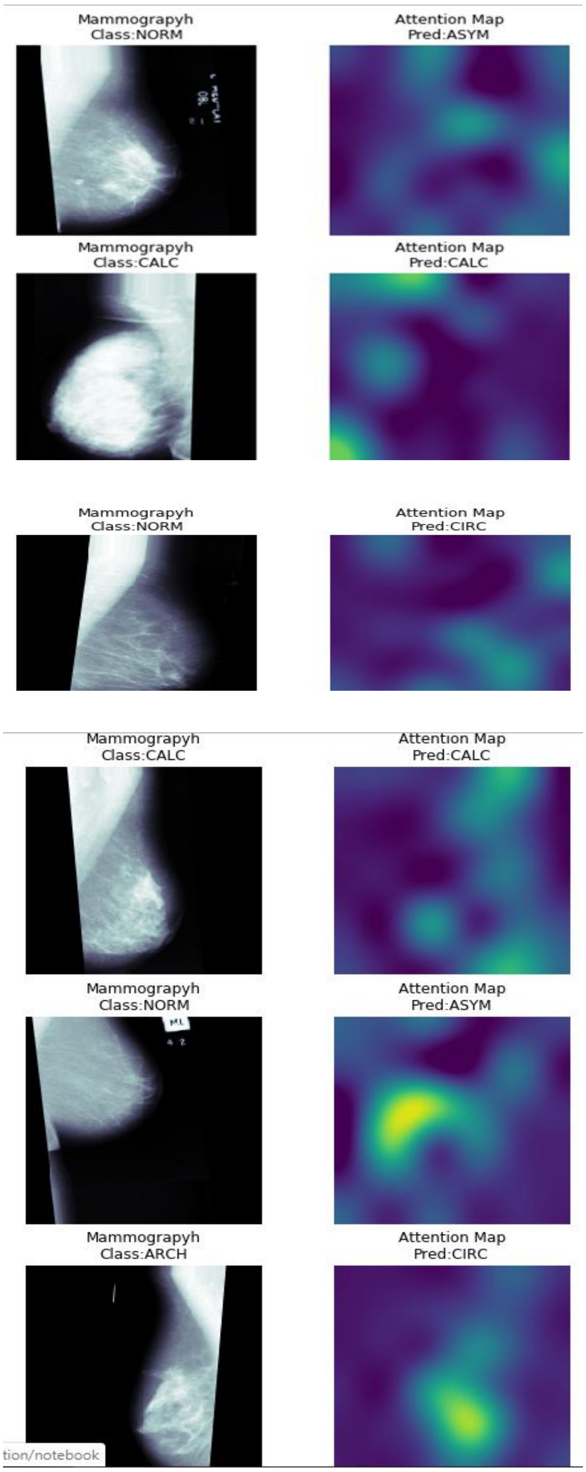

Figure 11. Predicted class of the mammography scan images vs the actual class of the mammography scan images with a viridis heat map overlay localizing the malignancy feature on the breasts.

VI. EVALUATION OF OUR ATTENTION LEARNING MODEL

Table I. Evaluation metrics and classification report for the performance of our classifier.

Classes	precision	recall	f1 score	support
ARCH	0.00	0.00	0.00	5
ASYM	0.11	0.33	0.17	3
CALC	0.28	0.88	0.42	8
CIRC	0.19	0.50	0.27	6
MISC	0.18	0.50	0.27	4
NORM	1.00	0.08	0.14	52
SPIC	0.23	0.60	0.33	5
micro avg	0.24	0.24	0.24	83
macro avg	0.28	0.41	0.23	83
wt. avg	0.69	0.24	0.19	83

Metrics such as precision, recall and f1 score are computed and displayed for our model based on its performance on the test data. Precision is the ratio of number of relevant instances to the total number of retrieved instances, in layman's terms it is a representative measure of the false positive misclassifications. If the number of false positive misclassifications under a particular class are high then the precision for that particular class would be low. Recall is the ratio of the number of relevant instances retrieved to the total number of relevant instances. It is a representative measure of the false negatives misclassifications. If the number of false negative misclassifications under a particular class are high then the recall for that particular class would be low. F1 score is the harmonic mean of precision and recall. It represents the accuracy of the classifier model on completely randomized data. The value of F1 score ranges in [0,1]. A higher F1 score within this range for a particular class is representative of a good classification accuracy with respect to the images belonging to that particular class. The support value for each class is the

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

number of test images under that particular class that have been accurately classified either as true positives or true negatives.

Upon close inspection of the precision, recall, f1 score and support values for each class, we observe that the classification accuracy for the CALC, CIRC, MISC & SPIC mammography classes are high and this in turn represents the good performance of the classifier model with respect to the classification of the mammography images belonging to these classes. The classification accuracy of the classifier for the ASYM & NORM classes could be improved and isn't reliable enough with lower values of precision, recall & f1 score.

The weights of the model are downloaded and the model as such is saved as a .h5 file which can then be loaded back into the workspace without the need to train it again from the beginning.

VII. ADVANTAGES

- Malignancy localization helps in accurately locating the region of the tumor.
- Attention learning model focuses on few specific pixels of the image from which the malignant feature had been extracted.
- Lesser utilization of resources such as RAM & GPU for processing the vast amount of training images due to application of pre trained keras models for feature extraction.
- Faster processing and a lesser processing time.
- Easier to visualize the position of the tumor in the breasts due to the heatmap overlay.

VIII. OUR UNIQUE APPROACH TO THE SOLUTION, PLANNING AND EXECUTION

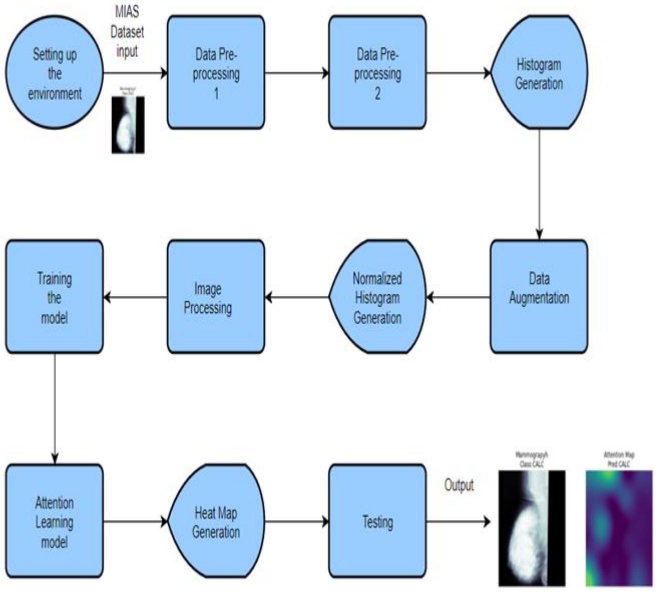

Figure 12. Our unique strategy in a sequential manner from the setting up of environment to the application of our attention learning classifier on our test data.

IX. POSSIBLE FUTURE DEVELOPMENT SCOPE

- Scaling the classifier to a larger dataset such as the DDSM imaging dataset which has more unique training instances than the augmented MIAS dataset.
- Utilizing a different fine-tuned CNN model with more hidden layers such as the RESNET50 to check if it yields a better feature extraction than the VGG16 NET and compare the results between different fine-tuned models.
- Adjusting the hyperparameters such as the loss function, optimizer etc. to improve the performance of the classifier on the test data.
- Utilizing a LSTM in the decoder circuit instead of a generic RNN to ensure that the context retention and filtering is more pronounced which in turn would lead to a more accurate weight adjustment from the feedback.

X. CONCLUSION

Malignancy localization is a crucial part of tumor diagnosis. Provision of specific attention to the pixels associated with the tumor and simple visualization of the same can help us infer from the mammography scans. An encoder-decoder architecture is used for the same wherein the CNN performs the functionality of the encoder by extracting the malignancy features from the scans and the RNN performs the functionality of the decoder by assigning & adjusting the weights for the extracted features based on the feedback received over a number of iterations. A heatmap overlay may be used to visualize the region of malignancy. The classifier is trained using the augmented training data of mammography scans and is tested by predicting the classes of the mammography images in the test data along with the application of attention mechanism on the images in the test data whose classes have been predicted by the classifier.

REFERENCES

[1] Zaiane, Osmar R., Maria-Luiza Antonie, and Alexandru Coman. "Mammography classification by an association rule-based classifier." Proceedings of the Third International Conference on Multimedia Data Mining. Springer-Verlag, 2002.

[2] Beura, Shradhananda, Banshidhar Majhi, and Ratnakar Dash. "Mammogram classification using two-dimensional discrete wavelet transform and gray-level co-occurrence matrix for detection of breast cancer." Neurocomputing 154 (2015): 1-14.

[3] Yoon, Sejong, and Saejoon Kim. "AdaBoost-based multiple SVM-RFE for classification of mammograms in DDSM." BMC medical informatics and decision making 9.1 (2009): S1.

[4] Nithya, R., and B. Santhi. "Classification of normal and abnormal patterns in digital mammograms for diagnosis of breast cancer." International Journal of Computer Applications28.6 (2011): 21-25.

[5] Balleyguier, Corinne, et al. "BIRADS™ classification in mammography." European journal of radiology 61.2 (2007): 192-194.

[6] Suckling, J., Parker, J., Dance, D., Astley, S., Hutt, I., Boggis, C., Ricketts, I., et al. (2015). Mammographic Image Analysis Society (MIAS) database v1.21 [Dataset].

[7] Rebecca Sawyer Lee, Francisco Gimenez, Assaf Hoogi, Daniel Rubin (2016). Curated Breast Imaging Subset of DDSM. The Cancer Imaging Archive.http://dx.doi.org/10.7937/K9/TCIA.2016.7O02S9CY

AUTHORS PROFILE

Ms. Manaswini Nagaraj is pursuing Bachelor of Technology in Computer Science Engineering at REVA University, Bangalore, India. She has worked as a Teaching Associate, Data Analyst and Product Developer at Corporate Gurukul, Singapore. Former Academic intern at National University of Singapore and HPE. Her main research work focuses on Machine Learning, Deep Learning, Blockchain and Big Data Analytics.

Mr. Vignesh Prabhakar, is a undergraduate student and researcher in deep learning & healthcare analytics at SRM University, former teaching assistant at National university of Singapore, Teaching associate and product developer at corporate gurukul, former tech member of google developer students chapter at SRM University, former member of SRM - center for applied research in education , former intern at SRM medical college hospital and research center, former Android developer intern at Uniq technologies.

Ms. Sailaja Thota received her B.Tech degree from Nagarjuna University in 2000, M. Tech. degree in Power Electronics from Visveshwariah Technological University in 2013.She is currently pursing Ph.D. and currently working as Assistant Professor in School of C & IT since 2010.She has experience of 14 months in IT,9 years of teaching experience and 3 years of Research experience. She is a member of ACM and IEEE. Her research interests are Data Mining, Machine Learning and Image Processing. She has published 8 papers in international journals (1 Scopus indexed) and 2 national conferences.