

# Mammogram Classification for Malignancy Localization Using Attention Learning

<sup>1</sup>B.Krishnakumar, <sup>2</sup>K.Kousalya, <sup>3</sup>S. Madhumitha, <sup>4</sup>P. Karthikaa, <sup>5</sup>T. Loghapriya

<sup>1</sup>Assistant Professor, Professor, <sup>2</sup>Kongu Engineering College  
<sup>3,4,5</sup>UG Scholar, Kongu Engineering College

**Abstract:** Mammography is an x-ray imaging method used for breast examination.. It is a specially designed medical imaging procedure to detect breast cancer at their early stage. A mammography exam report, called the mammogram assists in early identification and diagnosis of breast cancer. This project intends to classify the mammography test scan images into their corresponding classes and uses a model which combines both CNN and RNN, called attention learning to locate specific pixels of tumour using a heat map overlay. Attention learning classifier model is a classic encoder-decoder circuit where convolutional neural networks carry out encoding and recurrent neural networks carry out decoding. Convolutional neural extract features from the mammography scans which is then fed into a recurrent neural network that concentrates the malignancy region based on continuously adjusting the weights by receiving feedback over several iterations. Mammography images are normalized, enhanced and augmented before feature extraction and assign weights to them as a part of pre-processing steps. This procedure would most importantly assist in tumour localization in the case of breast cancer.

**Index Terms:** Convolutional neural networks, Recurrent neural networks, Attention Learning mechanism, Encoder-Decoder circuit, Mammography.

## I. INTRODUCTION

Mammography is utilized for breast assessment to determine the presence of breast cancer. There are a several malignancy classes in the scan images. Typical collection of open source clinical imaging, mammography dataset contain seven distinct classes of breasts in mammography. Tumors related with any of these classes could be either malignant, benign or normal. To find the scope of tumor in the mammography scans, we need to perform feature extraction from an assortment of closely related images pixels and accredit weights to the features themselves which can be renewed through backpropagation for the purpose of providing attention to several selective features which represents the region of malignancy. This process is accomplished through an encoder-decoder circuit which combines convolutional neural network and an recurrent neural network. After the classifier has been built and trained on the training dataset of mammography scans, it tends to predict the classes of the mammography images in the test data. The malignancy region can be visualized by incorporating heat map overlays. Metrics of evaluation and a classification report is engendered to monitor the efficacy of the classifier's performance on the test dataset.

Thus, the model could be used a diagnostic tool to elaborate the mammography report to the patient who is affected.

## II. LITERATURE SURVEY

The literature survey conveys the previously proposed research work on measures adopted in order to perform mammography images classification for the diagnosis of malignancy related with each scan.

Classification based on multiple association rule (CMAR): This method states a neural network classifier. The nodes which are in the input layer represents one characteristic from each rule. The number of input nodes are equal to the number of characteristics. Number of hidden layers are equal to the number of rules and the number of output nodes are equal to the number of mammography classes. To learn the network with a 10-fold cross validation and sigmoid activation function, backpropagation is used. In order to measure the performance of the classifier, ROC curve is drawn by calculating and plotting the sensitivity and specificity.

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-efficient from 2D- discrete wavelet transformation of the region of malignancy. The relevant features are derived through f-test and t-test of random sampling. The area under the receiver operating characteristic (ROC) curve is better. The accuracy of this model is awkwardly high owing to the absence of measures to avoid overfitting. Weight assignment to the features represents the region of malignancy. Weight adjustment which can be attained from the feedback is absent, so giving attention to a specific feature is not possible [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. SVM-RFE sorts the features in working set in the order of distinctions between objective functions and the features are removed with minimal distinction. The method called, ensemble is used to merge SVM-RFE with the boosting approach to perform replication of original dataset by random resampling to yield a higher improvement. 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, fibroglandular 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].

Classification of mammography scan images into one of seven classes and identification of tumour malignancy region using image data from Mammographic Image Analysis Society (MIAS). In this model, convolutional neural network and recurrent neural network are combined to perform the task. This method is stated as Attention Learning. When CNN performs the encoding part and extract the features from images and RNN performs the decoding part and finds the malignancy location by updating weights through backpropagation. This has produced a pronounced f1-score of 0.19, with higher classification accuracy for CALC, CIRC, MISC & SPIC[6].

### III. PROPOSED METHOD

The intention of the paper is to propose a technique which classifies the mammography scans into the classes to which they belong to and give attention to the region of malignancy.

#### A. Technical Specifications

The technical facets of the proposed methodology include:

4 GB allocation of RAM

Open source datasets for mammography from Kaggle

Services that offer python3 notebook with all the needed packages and libraries installed and ready to be imported

Tesla K80 GPU

### B. Dataset

The innovations that emanate in mammography images classification requires datasets with a broad range of images. These datasets can be spawn by gathering images of format .pgm inside a specific folder which is further continued by compression of the images for purpose of making them easily available for later usage.

MIAS Dataset: The Mammographic Image Analysis Society is an open source dataset, which has 322 peculiar breast scan images. They are available at a resolution of 50 microns in Portable Grey Map (.pgm) format[7].

## IV. METHODOLOGY

### A. Summary of the sequence of activities:

The array of activities for engendering and training the classifier for the sake of accurately classifying the mammography test scan images, which is further continued by applying the mechanism of attention learning for localization of tumour in the same is indicated below:

### B. Pre-processing of data:

The mammogram scan images are available in the Mammographic Image Analysis Society (MIAS) dataset in which the images are in Portable Grey Map (.pgm) format, which is consequently converted to its corresponding Tagged Image File

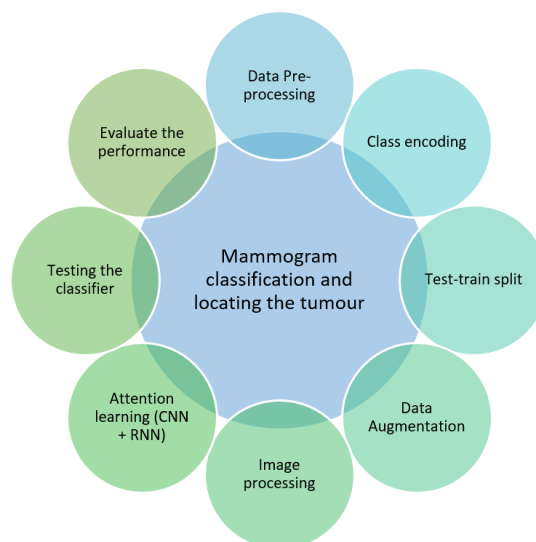


Figure 1. Module-wise application for classification of mammograms using attention learning model

	BG	CLASS	RADIUS	REFNUM	SEVERITY	X	Y	PATH	SCAN
28	F	CIRC	56.0	mdb028	M	338.0	314.0	mdb028.pgm	tiffs/mdb028.tif
175	F	NORM	NaN	mdb173	NaN	NaN	NaN	mdb173.pgm	tiffs/mdb173.tif
124	G	ARCH	33.0	mdb124	M	366.0	620.0	mdb124.pgm	tiffs/mdb124.tif
309	F	NORM	NaN	mdb302	NaN	NaN	NaN	mdb302.pgm	tiffs/mdb302.tif
240	D	NORM	NaN	mdb235	NaN	NaN	NaN	mdb235.pgm	tiffs/mdb235.tif

**Figure 2. The pre-processed dataset with the related attributes after converting the pgm format images to tiff format images.**

Format (.tiff) using the exclusive path allocated to individual pgm formatted scan images to aid the pre-processing. This process in this procedure is carried out to facilitate the processing of images which is comparatively perplexing in the case of images in portable grey map format. These instances which are in the tagged image file format are saved in a separate column in the dataset. The different attributes in the pre-processed dataset are figured out and inferred. Figure 2 shows the randomized, pre-processed dataset after the conversion of .pgm format to .tiff format.

### C. Class Encoding:

The mammography scans each of which has different classes are analyzed, understood and an uncommon class identity number is designated to each one of them. Consequently label encoding is implemented on the dataset. Applying label encoding onto the dataset equips an extra column in the pre-processed dataset namely the class identity number which has numerical figures from 1 to 7 which represents the class which each mammography scan image belongs to. The seven mammography classes are as follows:

#### Architectural Distortion (ARCH) :

This class contains images in which the normal architecture of the breast is found distorted with no visible mass.

#### Asymmetry (ASYM) :

Breast asymmetry means that the breast is in different size or shape than the normal breast. It changes the density of the breast. This class contains images of this type.

#### Calcification (CALC) :

The calcium deposits within the breast tissue appear as white spots or flecks in the mammogram, are called the breast calcifications. The images under this class reflects these characteristics.

#### Circumscribed masses (CIRC) :

Circumscribed masses can either be benign or malignant. If the contour of the breast mass is smooth and round, then it is benign. If the contour of the breast mass appears irregular in shape, then there is a greater likelihood of malignancy. The images in this class has these findings in them.

#### Normal (NORM) :

In this class, the image of breast appears normal without any defined masses or spots.

#### Miscellaneous (MISC) :

Miscellaneous breast images contain other, ill-defined masses. They may or may not be cancerous.

#### Spiculated masses (SPIC) :

The images under this class, has breast with a lump of tissue with spikes or points on the surface.

Further, a class vector attribute is added up to the dataset. Each entry under this attribute contains a vector of six zeros that depicts the void of a distinct class and the number one that denotes the presence of a class. The index positions of the class vector and the class identity number correspond to one another.

PATH	SCAN	CLASS_ID	CLASS_VEC
mdb299.pgm	tiffs/mdb299.tif	5	[0.0, 0.0, 0.0, 0.0, 0.0, 1.0, 0.0]

**Figure 3. The attributes appended to the pre-processed dataset after carrying out label encoding process on the mammography images**

In Figure 3, the attribute CLASS\_ID indicates that the image belongs to the 5<sup>th</sup> class (i.e. NORM) and the attribute CLASS\_VEC has the value 1 in the 5<sup>th</sup> position and void elsewhere.

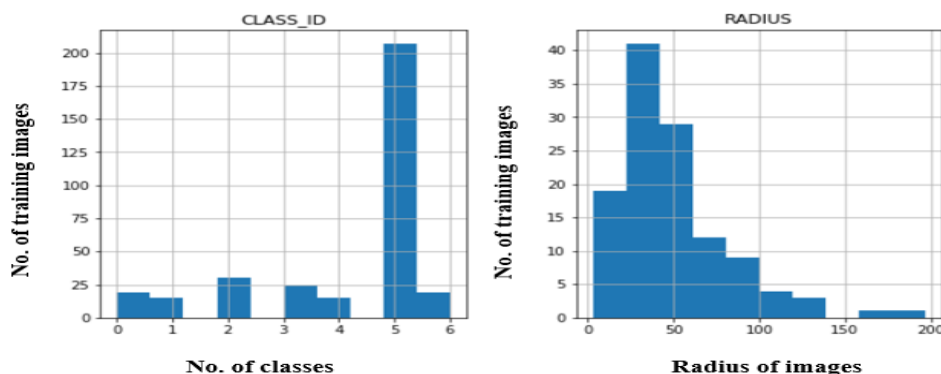
#### D. Test Train split:

train 247 validation 83

**Figure 4. Number of training images instances vs the number of testing images instances after carrying out the train-test 75-25 split.**

Subsequently, the separation of testing dataset and training dataset is done by giving 25% of the dataset with intention of testing and the remaining 75% with intention of training the classifier. This is done on account of ensuring increased availability of data for training purpose which in turn would generate a much accurate model. Prior to performing the split, the whole dataset should be randomized and it is necessary.

Histograms which examine in contrast the number of instances of the training images for each class identity is plotted to observe the number of instances for training under each mammography class before data augmentation.



**Figure 5. Number of instances applicable for training concerning each class ID number before data augmentation**

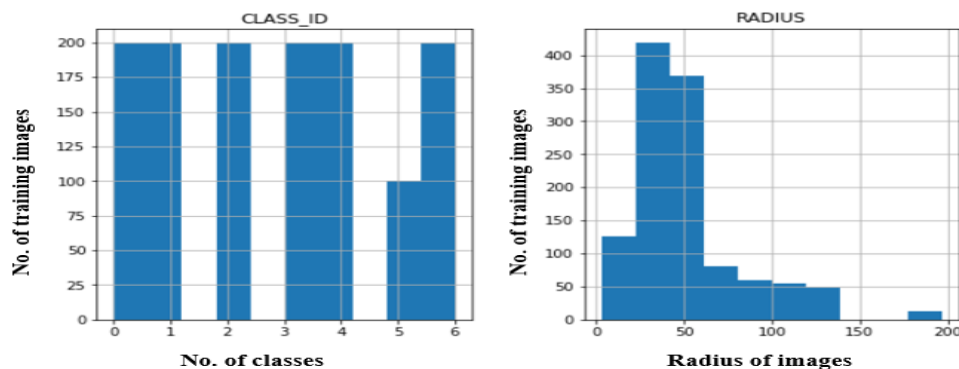
#### E. Data Augmentation

New Data Size: 1300 Old Size: 247

**Figure 6. Number of training image instances available after augmentation of data while preserving the 75-25 train-test data split.**

Following test-train split, data augmentation is carried out on the training images dataset to increase the quantity of images that are usable for training, to refrain from any inherent bias that may occur during the classification of mammography scan images owing to the inadequacy in training images under one or more class.

After augmentation of data, the histograms which shows the number of training instances for each and every class ID is plotted against and identical heights of the bars can be seen in the histogram which clearly shows the rejection of inherent bias in the instances assigned for training under each class of mammography.



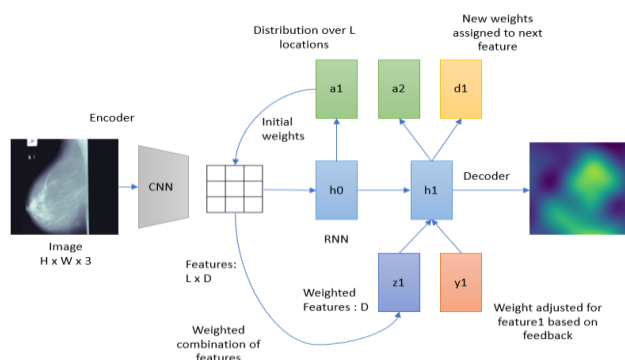
**Figure 7. Number of instances applicable for training concerning each class ID number after data augmentation**

#### F. Image processing to remove noise and loss of information:

Once the data is all set and ready for processing, the images are all shaped by normalization into a similar facet of 196x196 pixels to phase out any extraneous noise and information loss that may occur during processing. The images which are normalized are processed in batches of size 16, 256, 1024 and restored into the data frames which are allocated for testing and training purposes. After the task of re-insertion of images is accomplished, the images which are processed from the training data frames are jotted down to guarantee the successful culmination of normalization and storing back the images in their respective data frames.

#### G. Neural Network Architecture and Technical Details

The mammogram images are rescaled and converted to 224 x 224 x 3 input format as it is need for the VGG16 Convolutional Neural Network (CNN) architecture. This CNN has 16 hidden layers with very small 3 x 3 convolutional filters and it allocates the likelihood of belongingness for the image given as the input regarding to each class depending on the extracted features. The class analogous to the maximal probability of belongingness is picked as the class for



**Figure 8. The Neural Network architecture employed to train the classifier**

the given mammography scan image. After the classification exemplar has been fixed, the feature matrix  $L \times D$  which corresponds to that specific class is given as input to the Recurrent Neural Network (RNN) architecture. The input layer of this RNN takes into account the features extracted from the feature matrix ( $x_i$ ) one after the other and accredits initial weights to those features ( $w_j$ ). The weighted sum is calculated by the formula given below:

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

The weighted sum which was the result obtained by applying the formula above is updated in the feature matrix ( $L \times D$ ) for each of the feature. The new, updated feature matrix is employed in the subsequent layer in the Recurrent Neural Network to compute the weighted sum again so as to update the feature matrix similar to that was done previously. Throughout the 6 hidden layer in the RNN, the same method is repeated. The anticipated malignancy feature values and the computed feature values from the final, updated feature matrix are set side by side at the output layer, whose squared difference is backpropagated as error from output layer to the input layer through the hidden layers. Based on the error values, new initial weights are assigned to the features and the whole process is redone for a total of 15 epochs. At last, that is, on completion of the 15<sup>th</sup> epoch, all the malignancy features are well mastered. The attention map, also known as the heat map is enforced over the pixels.

## H. Malignancy localization using Attention Learning

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

A fine-tuned Convolutional Neural Network architecture ImageNet (VGG16) is used to carry out the classification of mammograms to engender labels for the scan images in the testing dataset. The weights of the final layers are available readily due to the pre-trained nature of the model. It is just integrated with the weights of the other layers, which is computed by the model. Usage of this kind of pre-trained model, reduces the processing time and also, it helps if there is insufficient computational resources in the case of availability of huge data. The VGG16 architecture used is a visual geometric group with 16 hidden layers.

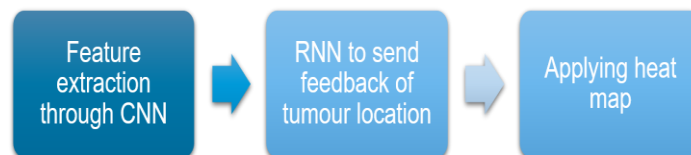
Initially, a CNN is built and is combined with the pre-existing architecture VGG-16 which performs the classification task and does the feature extraction.



**Figure 9.** Steps involved in fine tuning the CNN (Encoder circuit) using VGG16

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

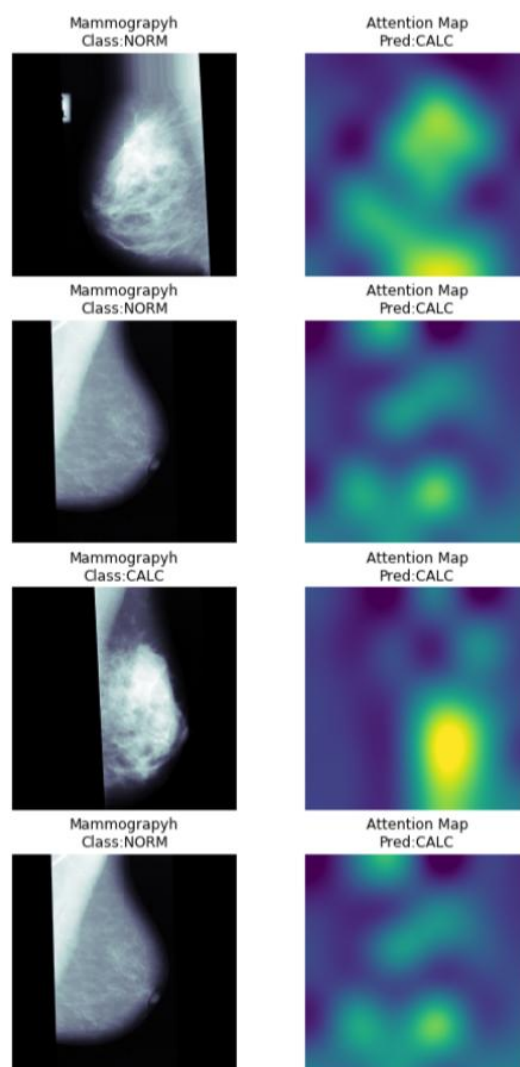
A Recurrent Neural Network (RNN) is used to determine the feature to be given at most attention in the mammography scan images by assigning and modifying the weights to the malignancy feature extracted by the Recurrent Neural Network through backpropagating over certain epochs of training. As a consequence, over the series of iterations, pronounced attention to the malignancy position is achieved. This feature which draws the maximum attention is the position of tumour malignancy.



**Figure 10. Incorporation of CNN (Encoder) with RNN (Decoder) circuit to attain Attention Learning model**

## V. TESTING THE ATTENTION MODEL CLASSIFIER

To illustrate the malignancy location in the mammography scan images, we make use of a Viridis overlay heatmap over the image to depict the mammography class as per prediction. Then, actual class of mammography is set aside with the predicted mammography class and is compared. The accuracy of the model is computed with the intention to judge the efficiency of the training and potency of the performance of the model over the test data.



**Figure 11. Predicted mammography class vs actual mammography class of the scan images with a ‘Viridis’ heatmap overlay which locates the tumour malignancy feature on the breasts**



## VI. EVALUATION OF ATTENTION LEARNING MODEL

Metrics for evaluation like precision, recall and F1 score are calculated and shown for the classifier depending on the effectiveness of the model over the test data.

**Table 1. Metrics for evaluation and classification report to determine the performance of the classifier**

CLASSES	PRECISION	RECALL	F1 SCORE	SUPPORT
ARCH	0.14	0.20	0.17	5
ASYM	0.20	0.67	0.31	3
CALC	0.31	0.62	0.42	8
CIRC	0.18	0.33	0.24	6
MISC	0.16	0.75	0.26	4
NORM	0.55	0.12	0.19	52
SPIC	0.11	0.14	0.14	5
MICRO AVG	0.24	0.24	0.24	83
MACRO AVG	0.24	0.41	0.25	83
WT.AVG	0.42	0.24	0.22	83

### PRECISION:

Precision is just termed as the ratio of number of relevant instances to the total number of retrieved instances, in amateur term, it is a classical measure of the false positive misclassifications. In case, if the number of false positive misinterpretations under a particular class are immense then the precision of that particular class would be low.

$$\text{Precision} = \frac{TP}{TP + FP}$$

### RECALL:

Recall is another term, which means the ratio of the number of relevant instances extracted to the total number of relevant instances in total. It is an epitome for the measure of false negative misclassifications. Here, in case if the number of false negative misclassifications are high, then recall of that class would be low.

$$\text{Recall} = \frac{TP}{TP + FN}$$

### F1 SCORE:

Another important measure is F1 score. It is the harmonic mean of recall and precision. It denotes the accuracy of the classifier model on entirely randomized dataset. It's range usually scale between 0 and 1. A greater F1 score within this bound for an individual class is representative of a good classification accuracy with respect to the images which belong to a specific class.

$$\text{F1 Score} = 2 * (\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision})$$

### SUPPORT:

Support value for each class is simply the number of test scan images which are present under a particular class that have been correctly classified either as true positives or true negatives.

When inspected closely, the metrics such as precision, recall, F1 score and support values for each mammography class, it is clear that the classification accuracy for the classes CALC, ASYM, MISC and CIRC are high when compared to the other classes. This, in turn denotes a good performance of the classifier with regard to the classification of the mammography scan images to their respective classes. The classes such as ARCH & NORM, whose accuracy could be enhanced further and is not decisive enough with reduced values of precision, recall and F1-score. This classifier produces an improved f1-score of 0.22 by adjusting the hyperparameters.

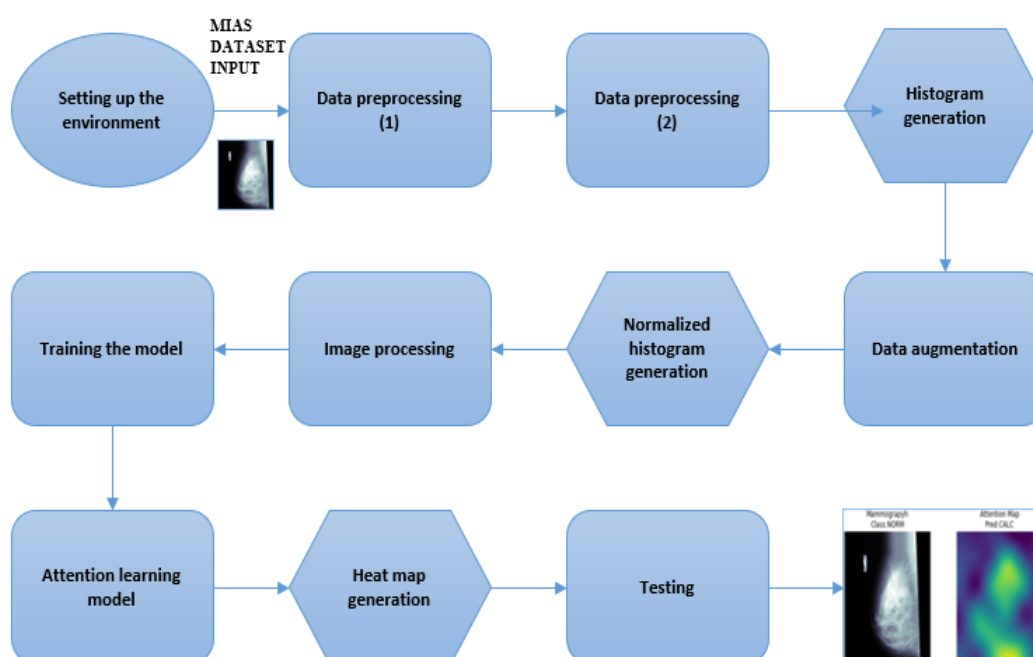
As it is difficult to train the model from scratch each time, the weights of the model are downloaded and it is saved as such in a .h5 file which can be further loaded back onto the workspace.

## VII. ADVANTAGES

Localization of malignancy helps in precisely locating the region of the tumour.

Attention learning model which combines CNN and RNN focuses on few specific image pixels from which the malignancy feature can be fetched. The utilization of resources such as RAM, GPU is lower for processing a huge amount of training images due to utilization of pre-trained Keras models for extracting features from the images. Faster processing even though the time required for processing is lesser. Effortless visualization of the tumour position in the mammography scan images of breasts due to the application of heatmap overlay.

## VIII. AN UNIQUE APPROACH TO THE SOLUTION AND IT'S EXECUTION



**Figure 12. An unique approach in consecutive manner right from setting up the working environment to applying attention learning approach to the testing dataset and generating output.**

## IX. POSSIBLE FUTURE DEVELOPMENT SCOPE

- Escalating the classifier to a much larger dataset like the DDSM dataset for mammography which has more peculiar instances for training rather than the MIAS dataset in which the amount of data is increased after augmentation is performed.
- Hyperparameters such as loss function, optimizer etc. can be fine-tuned to enhance the efficacy of the classifier on the test data.

- Making use of a different finely adjusted CNN model with more hidden layers such as RESNET50 to analyze if it brings about a better feature extraction than the already used architecture VGG16 and correlate the results between the different models.
- Applying a LSTM instead of using generic RNN in the decoder circuit to assure that the context retention and filtering is more distinct which would lead to a more exact adjustment of weights from feedback.

## X. CONCLUSION

In this paper, classification of breast mammography images and locating malignancy was done using the combination of CNN and RNN. The F1-score is chosen as an evaluation metric, as F1 score is not prone to class imbalance whereas test accuracy of classification can be misleading in nature, if the data is heavily skewed towards a tumour class that is correctly classified by the model vs another class that is not correctly classified by the model. The F1 score was improved to 0.22 from 0.19.

Localization of malignancy is the most crucial part of tumour diagnosis. Giving specialized attention to the pixels of the mammography scan images can help us understand the position of malignancy. Here, utilizing CNN and RNN together as encoder-decoder circuit is a novel idea where CNN does the job of encoder which is used to extract the features from the scan images and RNN does the job of decoder by assigning and calibrating the weights for the features extracted based on the feedback received over a number of iterations. A Viridis heatmap overlay may be applied over the images to visualize the malignancy. The classifier is trained over the training data and is let to predict the mammography class in the scan images. Here, due to repetitive adjustment of weights, attention is given to the malignancy location and hence, the classifier is found to classify the test scan images into their respective classes and also locate the tumour in the images.

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