Improvisation of Breast Cancer Detection using LSTM Algorithm

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Abstract - The impact of AI on healthcare is growing every day. A great deal of work is being done to improve the effectiveness of cancer diagnosis in its early stages, where medical imaging is essential. Breast cancer is alarmingly on the rise among women, with an Indian woman receiving a breast cancer diagnosis every four minutes. Even though breast cancer is treatable, early detection of the condition is crucial to a positive prognosis. Mammograms were once the only method for identifying breast cancer. Mammography, however, is ineffective for women of all ages, leading to an excessive number of false positive and false negative cases. This has severe effects. This experimental paper describes utilizing an LSTM (Long Short-Term Memory Network),deep learning technique to get around this constraint. It is an advanced recurrent neural network, that can solve the vanishing gradient issue, that the recurrent neural network encounters when attempting to identify the malignant region in mammograms. After receiving approval from the scientific and ethical committee, this experiment was carried out using the Real Time Data set of mammograms obtained from a hospital with 1250 beds. In this experimental study, a total of 1646 mammogram images from 414 patients were used. Among the real-time mammography data set, the LSTM algorithm provided a detection accuracy of more than 90% for the signs of breast cancer, by providing a relevant Bi-RADS score.

Keywords: Deep Learning, RNN, LSTM, Mammogram, Recurrent Neural Network, Long Shot-term Memory, Breast Cancer Detection.

I Introduction

Breast cancer is becoming increasingly prevalent in our nation, because of inadequate awareness campaigns and other factors. Although this cancer is easily diagnosable, it is thought to be the most common cancer [1] that causes fatalities. Among American women, this cancer comes in at number two [2]. Changes in lifestyle [3], as well as a lack of awareness among community women [4], are a few factors contributing to the rise. Typically, breast cancer cells form a lump that is palpable or visible on an x-ray. Though majority of breast lumps are not cancerous (malignant), which do not spread outside of the breast. Any lump or alteration in the breast should be evaluated by a healthcare professional to find any risk associated with that. Numerous research is conducted worldwide to understand the level of knowledge among women [5]. The most important methods for preventing breast cancer fatalities are early identification and progressive cancer treatment [6].

If a carcinoma is found early on, it can be treated. Early cancer diagnosis, when the disease is little and has not spread, makes treatment simpler. The best method for early breast cancer detection is routine screening exams [7]. The most popular screening technique is a mammogram, often known as a low-dose chest x-ray. Decades of study have shown that women who receive routine mammograms are recognized early [8], require less treatments like breast removal surgery (mastectomy), and are more likely to be cured. Mammograms can detect malignant abnormalities in the breast years before physical symptoms develop.

Mammograms do have a number of issues. Some cancers are difficult to identify. In certain rare cases, a woman will also seek more proof to determine whether a mammography finding is cancerous. After reviewing the mammogram, a radiologist is responsible for generating a report, which occasionally may be falsely positive or negatively indicative based on a variety of variables. However, by utilizing artificial intelligence, radiologists have been able to make a better proposal [9]. More precise diagnosis is promised by AI [10]. This study examines how the LSTM algorithm can help radiologists identify breast cancer from mammograms and make better decisions. By giving the radiologist extra machine input and identifying whether or not the mammography image contains malignant tissue, the model created using the aforementioned method can help reduce false positive and negative cases. and alters the precision of finding breast cancer.

II Literature Survey

Here are a few instances of experimental research that have identified breast cancer using Deep Learning methods: Yap et al [11] used the

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CNN method to find lesions in ultrasound images. The entire process was automated, and it was demonstrated that doing so increased the reliability of lesion diagnosis and decreased breast cancer mortality.

Similar to this, Q. Ping and his colleagues' work [12] uses the K-medoid clustering approach to gather and evaluate breast cancer data. In their experimental study, Both and his team of researchers [13] used Association Rule Mining and Neural Networks to identify breast cancer.

An innovative hybrid strategy for classifying cancer that combines decision trees with numerous other strategies was developed by Vosooghifard and H. Ebrahimpour [14]. In a different experimental inquiry, Wang et al. [15] offer a classifier to categorize cancer based on collaborative representation. In Chen et al, research, machine learning is used to identify and categorize cancer major locations [16]. In the experimental trials described in [17] [18], the authors created a scoring system to identify the presence of malignant cells in mammography pictures.

Few researchers used medical imaging modalities, to analyze breast images in the experimental study [19], which demonstrated that the accuracy of cancer symptom identification can be increased. To diagnose lung cancer, the authors [20] used machine learning techniques. Another study that was referenced, used deep learning and patch-level categorization to find lung cancer [21]. The patient undergoes a battery of tests if cancer is suspected before being checked for malignant tumor cells. Medical imaging techniques are provided by doctors to identify lung cancer. Imaging methods are useful for identifying suspicious areas, determining the stage of cancer, validating treatments, and spotting recurrence symptoms in cancer cells.

An end-to-end breast cancer detection method was created by a research team [22] to find breast cancer in mammography images. Finding cells is the first and most important step in the intended diagnosis of cancer.

In another similar study [23], the researchers used a hybrid methodology to integrate the CNN algorithm with other techniques, greatly increasing its efficacy. The application of machine learning methods for early detection is the main emphasis of the authors' study, which is presented in the paper [24]. Another comparable attempt at detection is made in the experimental study [25].

III Methodology

The several measures that have been done are explained in this section. A total of 1646 mammography pictures from 414 participants were used in this experimental study. Throughout the experimental investigation, there were numerous interactions with the radiologists working in the Father Muller Medical College Department of Radio Diagnosis and Imaging to better understand the process of detecting cancer through mammograms. The radiologist writes a report by examining all 4 mammogram images of a patient. they cannot just see one mammogram image and get to the conclusion. Each mammogram image has a link, and by examining all these possibilities radiologists write the report whether a patient has cancer or not, by writing the score of the cancer detection that is called the BI-RADS score. A BI-RADS score can range from 0 to 6.

Final Assessment Categories

	Category	Management	Likelihood of cancer
0	Need additional imaging or prior examinations	Recall for additional imaging and/or await prior examinations	n/a
1	Negative	Routine screening	Essentially 0%
2	Benign	Routine screening	Essentially 0%
3	Probably Benign	Short interval-follow-up (6 month) or continued	>0 % but ≤ 2%
4	Suspicious	Tissue diagnosis	4a. low suspicion for malignancy (>2% to ≤ 10%) 4b. moderate suspicion for malignancy (>10% to ≤ 50%) 4c. high suspicion for malignancy (>50% to <95%)
5	Highly suggestive of malignancy	Tissue diagnosis	≥95%
6	Known biopsy-proven	Surgical excision when clinical appropriate	n/a

Fig. 1: Bi-RADS Score and its Likelihood of Cancer

As it says >3 is malignant which means cancerous and <3 and >0 means benign that means non-cancerous cell. And 0 means that the radiologist ware not able to spot any cells due to extreme dense of breast in such case they suggest sono-mammogram which is an advancement of mammogram.

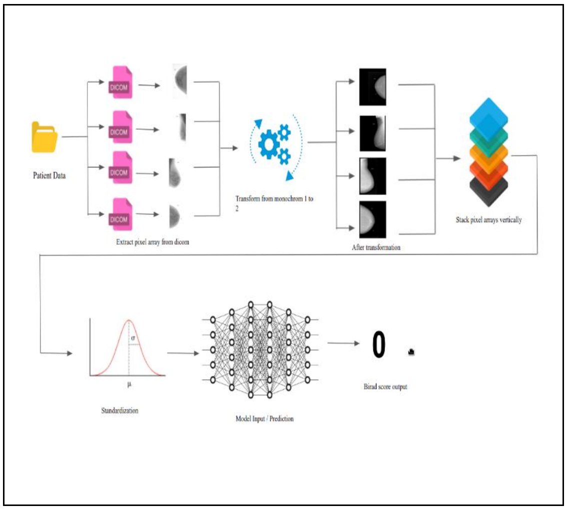
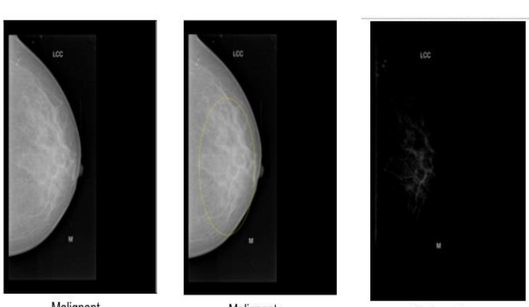


Fig. 2: Breast Tumour Detection using LSTM Algorithm.

As the data of 414 patients were collected, their relevant reports, were also collected and the mammogram images were labelled with the BI-RADS score for training. The proposed framework explains how the Mammogram, which is a DICOM image, is annotated by the Radiologist and the system is trained to identify the Cancerous cells in the Mammogram. Once annotated and trained, the algorithm can detect the Cancerous cells in the Mammogram, which helps the radiologist to fine tune his diagnosis. This system is trained to give you the relevant Bi-RAD score as the output. As described in the above fig. 2, First, it is collecting data from a folder of each patient, and each folder has 4 dicom files. After that, extracting pixel array from each dicom files and checking whether it’s a monochrome1 or 2, if it’s a monochrome 1 then transform that to monochrome2, and after transforming stack the 4 dicom pixel array vertically and make it as one whole array, then standardize the array. After standardization, input the array to the model and finally the model will predict the BI-RADS score.

A.Sources of Mammograms

The Mammography Images were taken from the Department of Radio Diagnostics and Imaging of the Father Muller Hospital in Mangalore., a total of 1646 mammogram images from 414 patients were used. All the relevant Reports were also taken from the department and the concerned diagnosis that was made was taken into consideration, before the annotation was made. Since the reports were having Bi-RADS score, this experimental study was designed to predict the relevant Bi-RADS score.



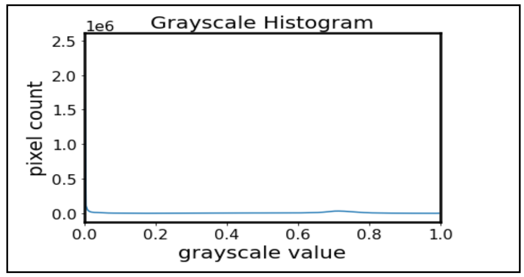


Fig. 3: Sample Images of Mammograms

B.Data Pre-processing:

After receiving the mammogram Dicom format Images, they were annotated and labelled. The shape of the mammogram, is elaborated below.

```
Type of the image :  <class 'imageio.core.util.Array'>
Shape of the image : (2048, 2048, 3)
Image Hight 2048
Image Width 2048
Dimension of Image 3
```

Fig. 4. Shape of Mammogram

The ndarray's geometrical structure reveals that it is a three-layered matrix. Here, the length and width are represented by the first two numbers, and the third number, or 3, represents the Red, Green, and Blue layers. In order to get the size of an RGB image, it must multiply the height by the breadth by three.

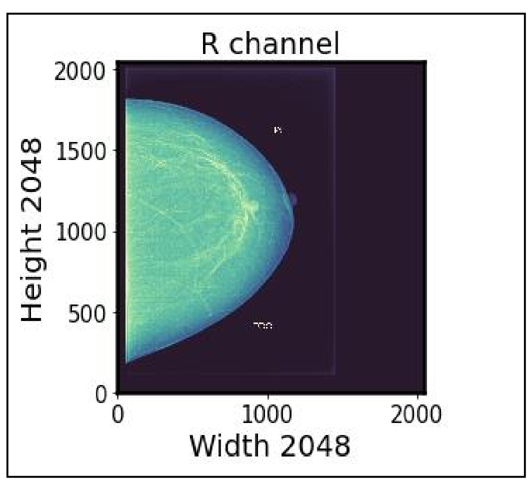


Fig. 5. R-Channel of Mammogram

Fig. 6. Histogram Representation of the Image

Image thresholding is a straightforward but efficient technique for separating an image's foreground from its background. By transforming grayscale photos into binary images, this image analysis technique is a sort of image segmentation that isolates objects. The best photos for image thresholding are those with high contrast levels. The same threshold value is used for each pixel. The pixel value is set to 0 if it is below the threshold; otherwise, it is set to a maximum value. The thresholding is applied using the cv. threshold function. The source image, which must be a grayscale image, is the first argument. The threshold value, which is used to categorise the pixel values, is the second input. The maximum value that is assigned to pixel values that are higher than the threshold is the third argument.

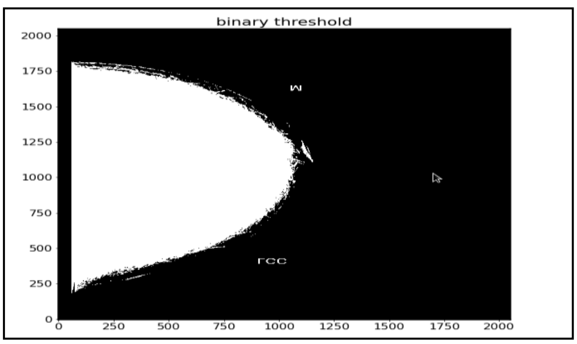


Fig. 7. Binary threshold of the Image

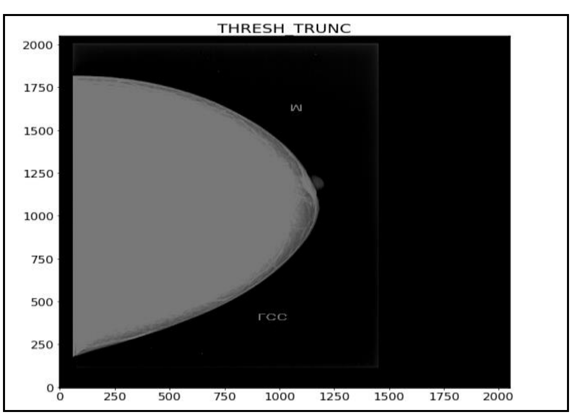


Fig. 8. Thresh Truncated of the Image

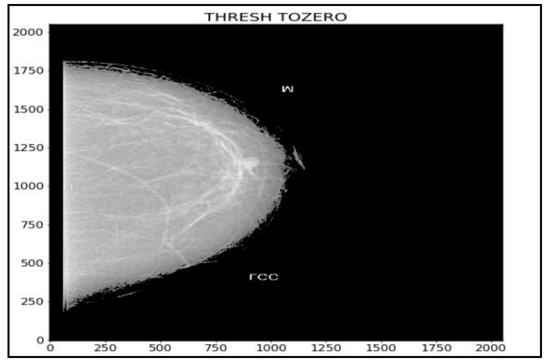


Fig. 9. Thresh Tozero of the Image

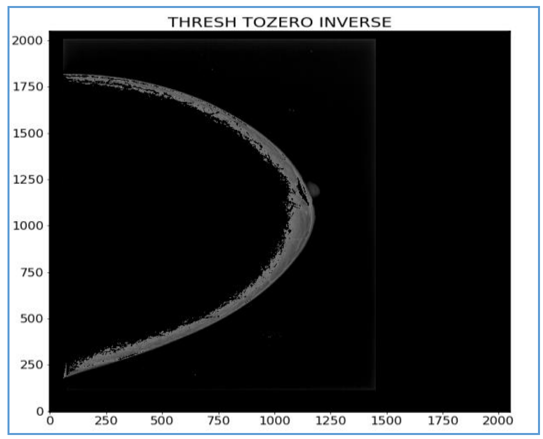


Fig. 10. Thresh Tozero Inverse of the Image

Consider a bimodal image, which has just two different image values and a histogram with just two peaks. Between those two numbers would be a reasonable barrier. Similar to this, Otsu's approach uses the image histogram to estimate the ideal global threshold value. To do this, the cv. threshold() method is utilized, with the additional flag cv.THRESH OTSU being provided. The threshold value may be selected at random. The best threshold value is then discovered by the algorithm, and it is returned as the first output.

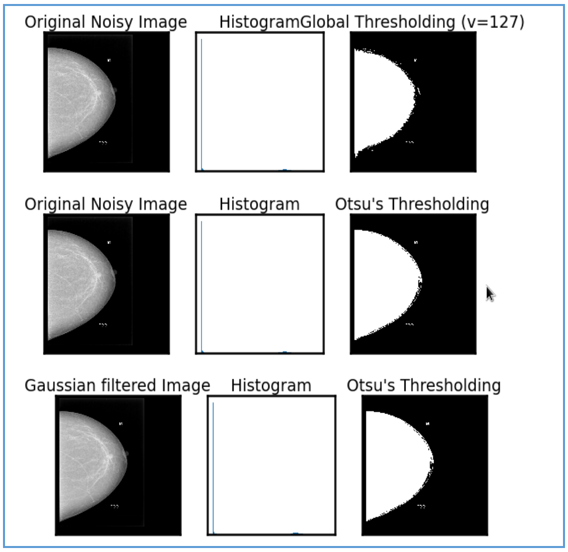


Fig. 11. Otsu's Binarization of the Image.

If there are various lighting conditions across an image. Adaptive thresholding can be useful in the situation. Here, a pixel's threshold is calculated by the algorithm using a small area around it. As a result, we obtain various thresholds for various areas inside the same image, which produces superior outcomes for photos with changing lighting.

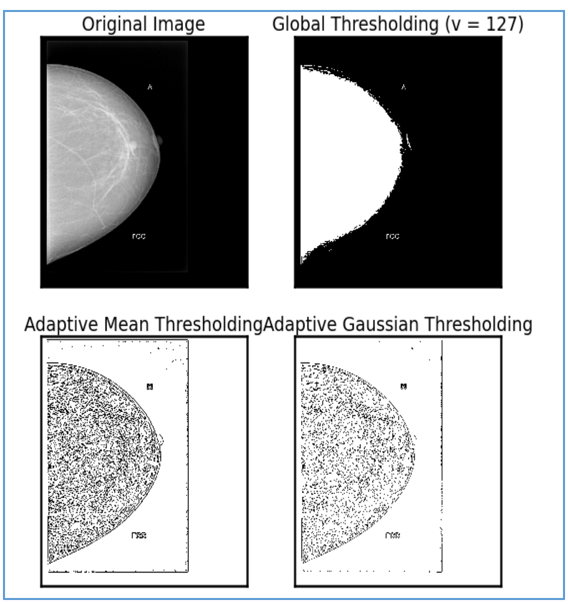


Fig. 12. Adaptive Thresholding of the Image.

C.Deep Learning techniques to detect Tumour cells

1. LSTM:

A subset of machine learning is deep learning, which is only a neural network with three or more layers. These neural networks attempt to mimic how the human brain works, but they are unable to match it, allowing it to "learn" from enormous amounts of data. Even though a neural network with only one layer can still produce approximation predictions, more hidden layers can help to tune and improve for accuracy.

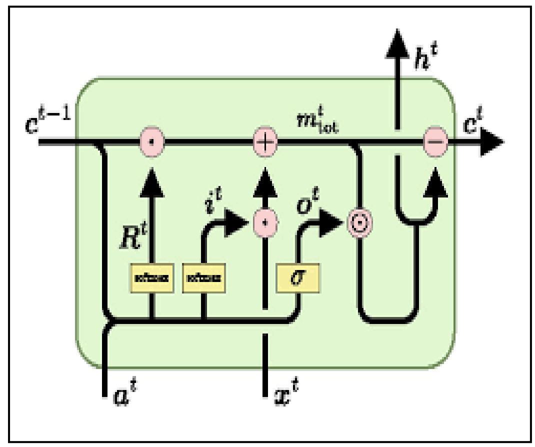


Fig. 13: LSTM Architecture

The long short-term memory network is a more advanced RNN, or sequential network, that allows for information persistence. It can fix the vanishing gradient problem with the RNN. Recurrent neural networks, often known as RNNs, are used for permanent memory. The three parts that make up the LSTM each serve a specific function.

The first part decides whether or not the details from the previous timestamp should be recalled. The second section's input to this cell is used by the cell to try and learn new information. Finally, the cell communicates the updated data from the third section's current timestamp to the following timestamp. These three LSTM cell constituents are mentioned by Gates. three gates: the forget, input, and output gates.

Similar to a standard RNN, an LSTM has a hidden state, with H(t-1) denoting the hidden state of the prior timestamp and Ht denoting the hidden state of the present timestamp. The timestamps C(t-1) and C(t), which stand for the past and current timestamps, respectively, are also used to indicate the cell state of LSTMs.

IV Results and Discussion

As you can see from the LSTM model's architecture, there are three levels. A dense layer is the final layer, while the prior two are LSTM layers. There are 6000 rows and 1500 columns in the LSTM's input shape. Each patient contains four DICOM files; for each file, the pixel value is extracted and the file is resized to 1500x1500. It employs stacked LSTM since the input size will be 6000x1500 if it is stacked vertically. An LSTM model made up of numerous LSTM layers is known as a stacked LSTM architecture. An LSTM layer above gives the LSTM layer below a sequence output rather than a single value output. One output time step for each input time step as opposed to a single output time step for all input time steps. Since the output is 4, the dense layer has four categories that are (incomplete assessment, normal study, benign and malignant). The LSTM model's executive summary is below.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 6000, 1500)        18006000
_________________________________________________________________
lstm_1 (LSTM)                (None, 1500)              18006000
_________________________________________________________________
dense (Dense)                (None, 4)                 6004
=================================================================
Total params: 36,018,004
Trainable params: 36,018,004
Non-trainable params: 0
_________________________________________________________________
```

Fig. 14: Summary of LSTM Model

The accuracy and the Loss of the LSTM model is elaborated below.

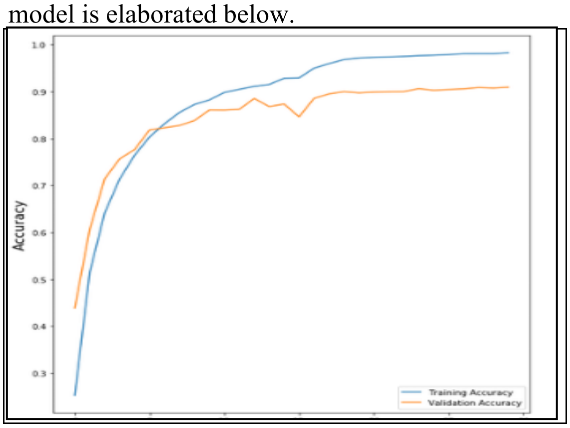


Fig. 15: Accuracy of the LSTM Model

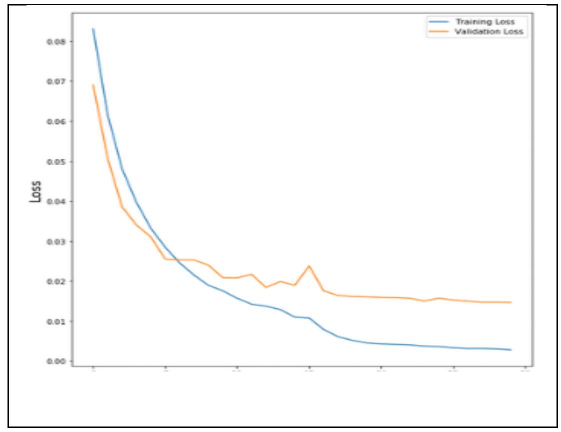


Fig.16: Loss of the LSTM Model

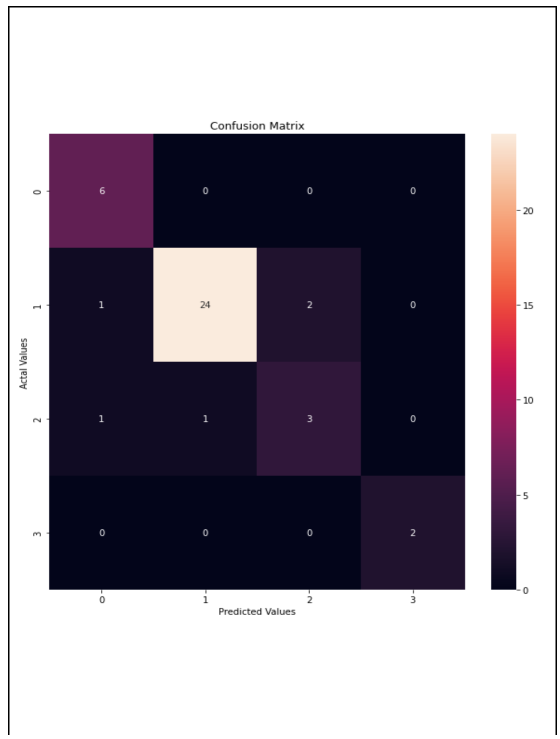


Fig. 17: Confusion Matrix of LSTM Model

Loss functions are important in statistical models because they provide a benchmark against which the model's performance can be judged, and the parameters obtained from the model are defined by minimizing a specific loss function. In other words, the loss function you select determines the estimator's quality. The goal of this study is to examine loss functions, their usefulness in validating predictions, and the many loss functions that are used.

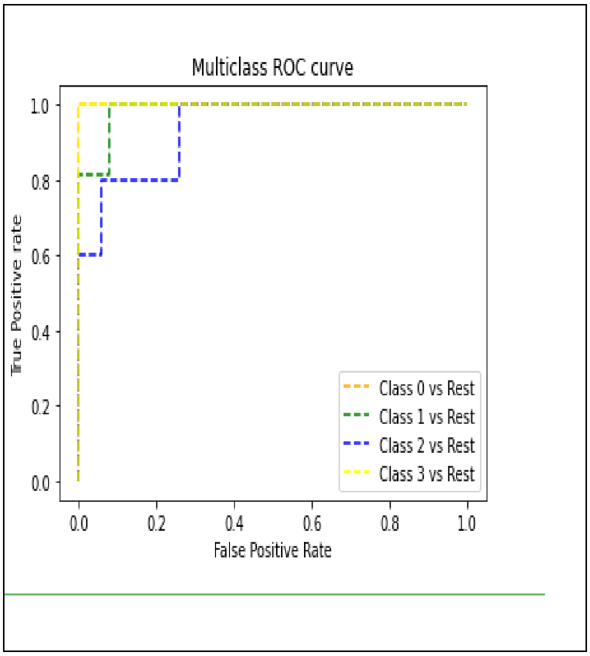


Fig. 18: AUC-ROC curve

Performance evaluation is a key role in machine learning. Thus, a classification problem can be solved using an AUC-ROC curve. AUC (Area under the Curve) ROC (Receiver Operating Characteristics) curves are used to verify or illustrate the performance of the multi-class classification issue. It can also be written as AUROC (Area under the Receiver Operating Characteristics), and it is one of the most crucial evaluation metrics for assessing the effectiveness of any classification model. Below is a more detailed explanation of the above model's precision, recall, F1-score, and support.

	precision	recall	f1-score	support
birad 0	0.75	1.00	0.86	6
birad 1	0.96	0.89	0.92	27
birad 2	0.60	0.60	0.60	5
birad 3	1.00	1.00	1.00	2
accuracy			0.88	40
macro avg	0.83	0.87	0.85	40
weighted avg	0.89	0.88	0.88	40

Fig. 19: Precision, Recall, F1-score for the LSTM Model

V Conclusion

The main goal of this research project is, examining how the LSTM algorithm can help the radiologist in assessing the mammography image and offer a BI-RAID Score. The achievement of this goal was demonstrated by the creation of a model that can identify the signs of breast cancer and provide a Bi-RAID score in accordance. When examining mammography images, the radiologist can utilize this model as guidance. The radiologist will also benefit from time savings while using this model to evaluate mammograms and write reports. This model will therefore support radiologists' decision-making when it comes to identifying breast cancer. The accuracy of the model can be improved by including more mammography images from various hospital settings and other locations in the training data set.

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