Analysing Breast Cancer using Convolution Neural Network

S. Vani Kumari[1], K. Usha Rani[2]

[1] Research Scholar, Department of Computer Science, Sri Padmavati Mahila Visvavidyalayam, Tirupati, Andhra Pradesh, India

[2] Professor, Department of Computer Science, Sri Padmavati Mahila Visvavidyalayam, Tirupati, Andhra Pradesh, India

Abstract: Technological development of Soft Computing and Artificial Intelligence contributed a lot towards disease diagnosis in medical science. For providing solutions to the biological inspired problems in medical domain like Breast Cancer (BC) soft computing methods can give the flexible information. As per 2020 about 2 million women were detected with Breast Cancer (BC) creating most common malignancy among women worldwide. This rises both incidence and mortality has occurred during the past three decades due to evolving risk factors, improved cancer registries, and earlier diagnosis. There is a large number of risk factors for BC, some of which can be changed and others cannot. Eighty percent of people diagnosed with BC nowadays are over the age of fifty. Molecular subtype and developmental stage are both important in determining the likelihood of survival. When it comes to clinical presentation, behaviour and shape, invasive BC span a broad spectrum of tumours. In this paper, Convolution Neural Network (CNN) used to recognize the BC tumor because it is another sort of neural network that can discover key information in both image and time series data. By applying CNN on the 2023 RSNA (Radiological Society for North America) Screening Mammography Breast Cancer data we analysed how best CNN algorithm is for identifying breast cancer with accuracy and also tried to analyse at what age Breast Cancer is mostly occurred in women.

Keywords: Breast Cancer, Convolution Neural Network, Tumor, Malignance, Patients.

1. INTRODUCTION

As per GLOBOCAN 2020 data [2] around 2.3 million new breast cancer cases are identified worldwide which makes breast cancer is the main cause of deaths in women. In transitioning states (Melanesia, Micronesia/Polynesia, Western Africa and the Caribbean), deaths from breast cancer are described at a higher occurrence (roughly 88% higher) than transitioned states (Western Europe, Northern Europe, Northern America, and Australia/New Zealand). Breast cancer incidence can be reduced and treated more effectively if a number of measures are taken, including general preventive behaviours and screening programmes. The Breast Health Global Initiative (BHGI) is currently in duty of developing an effective recommendation method for worldwide breast cancer control [3].

For successful treatment of breast cancer detecting it early is the main key. Therefore, it is crucial to have access to effective screening tools for identifying the first signs of breast cancer. Mammography, Ultrasonography and Thermography are among the most common imaging methods used in screening for this condition. When it derives to identifying of breast cancer in early stage, mammography is the most important clinical test. Insight of these concerns thermography and radiography may be useful than ultrasonography for classifying smaller malignant tumours [2].

In recent years the need to process the digital data created during medical diagnosis has led to the widespread adoption of Computer-Aided Diagnosis (CAD). Processing digital photos to extract crucial information and processing the information to identify the various phases of disease is critical for disease identification. As a result, biological data classification aids in disease diagnosis and prognosis [11]. Insight into data processing applications in numerous sectors using soft computing techniques has huge achievements in the field Cognitive Analysis of Healthcare Data [12]. Instruments consume remain procedure to create and expand image processing as a result of the inherent challenges associated with a picture such as low contrast, noise and under gratitude by the appreciation. To handle complicated tasks while decreasing reliance on human intelligence [1, 3-6], the healthcare industry is rapidly adopting CNN [1, 7-9].

This paper, main objective is to predict and analyse electronic cancer record and image data. To accomplish this Convolution Neural Network (CNN) is used to recognize the BC tumor because it is another sort of neural network that can discover key information in both image and time series data. By applying CNN on the 2023 RSNA (Radiological Society for North America) Screening Mammography Breast Cancer data. we analysed how best CNN algorithm is for identifying breast cancer with accuracy and also tried to analyse at what age cancer is mostly occurred in women.

The remaining of this paper is organized as follows: The second section deals with Literature Review, the third section describes methodology, the fourth section describes the Experimental Analysis, and the final section deals with conclusion.

2. LITERATURE REVIEW

CNN's potential benefits for research in medical imaging are not restricted to deep CNN for extraction of features. Indeed, the application of CNN synthetic image translation can aid in medical research as a second area. To aid in mitotic count selection of Reason of Interests (ROIs) at lesser resolution, appropriate colour and textural qualities are proven as shown by a study conducted by Wahab and Khan [14] using MF-CNN (Multifaceted Fused-CNN) and hybrid descriptor. Multiple features of the input image are recognised by the MF-CNN in order to identify moving patterns. Using the global image texture, extracts, mitoses and handcrafted from ROIs features are included into a hybrid descriptor that is then used to classify train and that assigns WSIs scores. CNNs are allowing for previously impossible use cases in fields wherever it is hard for domain specialists to project actual features. Naive usage of CNN may not be fruitful, as pointed out by Gravina et al. [15] because "medical images are more exceptional than normal images." It has remained unproven that mammographic lesion segmentation is a useful source of information, as it has the potential to aid in withdrawal of shape associated features offer precise lesion localisation.

Tsochatzidis et al. [16] conducted a research to see in what way CNN might detect breast cancer from a mammogram. They establish how diagnostic enactment is evaluated via mammographic mass datasets like CBIS-DDSM and DDSM-400, both of which exhibit variances in accurateness of their respective maps segmentation of ground truth. In edict to facilitate detection in early, evaluation and treatment of BC, Malathi et al. [17] using mammography implemented a Computer-Aided Diagnostic (CAD) system. They explained about CAD architecture investigation for breasts using CNN deep learning focuses on fusing characteristics. According to discoveries, RFA (Random Forest Algorithm) outstrips the CNN classifier with 95.65 percent accuracy. Using a Deep Belief Network (DBN) looked into the abnormalities in breast images potentially. Assigned tasks trigger outline segmentation which is requested from the DBN to recognize anomalous image. To determine which network is superior, Desai and Shah [18] noted that a thorough comparison of functioning and architecture for each network is executed with further analysis based on the accuracy with which each network diagnoses and classifies breast cancer. For matching CNN with Machine Learning Process (MLP), it is seen that CNN offers slightly higher precision for diagnosing and recognizing breast cancer.

Abdelhafiz et al. [19] found an augmentation technique was effective in automatically identifying the cancer. Mitosis pictures in breast histology were identified using deep max pooling CNNs by many researchers [20]. The networks performed adequately when asked to rank the photos by pixel. Murtaza et al. [21] engaged a Deep Learning (DL) method to automatically detect and examine IDC tissue zones. Hossain [13] demonstrated context-aware stacked CNN for the classification of breast Whole Slide Images (WSIs) into simple, DCIS (Ductal Carcinoma in Situ) and IDC. The system attained 81.3% of three-class accuracy for classification of WSI and an area in curve of 0.962 for classifying non-malignant and malignant slides. This demonstrates the technology's potential for regular diagnostics. Alhamid et al. [22], Qian et al. [23] both provided methods to distinguish them in their respective publications. The magnitude and phase of shearlet coefficients were shown to increase accuracy and generalizability as demonstrated by their experiments.

Several prior studies [12, 17, 19, 24, 27] have suggested combining AI with CNN for identification of picture and monitoring healthcare is useful. However, the percentage of accuracy is too low for medical solutions. Around 60% for identification of all class, only 75% for mass class and only 100% for clarification [25]. All arguments, save the clarification argument and the mass argument is improved upon the yield for a better result [26]. So, the key objective of this learning is to improve CNN's diagnostic accuracy for breast cancer. This researcher suggested a breast cancer diagnosis system based on number of regression and Deep Learning methods. In order to automatically diagnose the cancer, initially uses a basic CNN and then adds it to three various architectures, all of which were guided by a big dataset of about 275,000, 50 × 50-pixel RGB image patches. The quantitative findings are measured by validation tests.

3. METHODOLOGY

A methodology is a rationale and strategy of a research. It involves studying the methods used in the field and theories or principles behind them. For breast cancer prediction and analysis using electronic cancer record and image data is accomplished by using CNN because it can be astonishing achievements across a variety of techniques. The latest BC dataset is considered in the study which has not been experiment by researches so far.

3.1. Dataset Used

The latest 2023 RSNA (Radiological Society for North America) Screening Mammography Breast Cancer dataset is considered [28] which is collected in Australia and the United States. There is a comprehensive labelling, along with radiologists' assessments and subsequent pathology results for cases where malignancy is suspected. Figure 1 provides a visual description of the dataset.

```
Data columns (total 14 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   site_id                   54706 non-null  int64
 1   patient_id                54706 non-null  int64
 2   image_id                  54706 non-null  int64
 3   laterality                54706 non-null  object
 4   view                      54706 non-null  object
 5   age                       54669 non-null  float64
 6   cancer                    54706 non-null  int64
 7   biopsy                    54706 non-null  int64
 8   invasive                  54706 non-null  int64
 9   BIRADS                    26286 non-null  float64
 10  implant                   54706 non-null  int64
 11  density                   29470 non-null  object
 12  machine_id                54706 non-null  int64
 13  difficult_negative_case   54706 non-null  bool
dtypes: bool(1), float64(2), int64(8), object(3)
memory usage: 5.5+ MB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4 entries, 0 to 3
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   site_id        4 non-null      int64
 1   patient_id     4 non-null      int64
 2   image_id       4 non-null      int64
 3   laterality     4 non-null      object
 4   view           4 non-null      object
 5   age            4 non-null      int64
 6   implant        4 non-null      int64
```

Figure 1: Dataset Parameters

3.2. Convolutional Neural Networks (CNN)

Convolutional Neural Network (CNN) is a more advanced type of artificial neural networks (ANN) that is commonly used to extract features from grid-like matrix datasets. For example, visual datasets such as photos or films, where image patterns play an important role. Image patterns can be explored with the use of CNN. The patterns can be find in an image by convolving over it [26]. In the early stages of CNN, the network is able to identify straight lines and sharp angles. However, with support of our neural network, propagation of these patterns downward and start picking out increasingly subtle details as we delve deeper. This characteristic is what makes CNNs so good at object detection [25]. The suggested technique employs convolutional neural networks to identify breast cancer through photographic evidence.

As seen in Figure 2, a CNN architecture contains of 3 distinct layers: pooling layer, convolutional layer and fully connected layer.

- Every input neuron in a conventional neural network is linked to the layer below it, called the ***convolutional layer***. In CNN, hidden layer neurons is only linked to a fraction of the input layer neurons.
- To lower the feature map's dimensionality, we utilise a ***pooling layer***, or layer 2. Within the CNN's hidden layer, numerous activation and pooling layers will be present.
- Third, ***fully-connected layer*** is the finishing set of layer in a network. The outcome of the finishing Pooling/Convolutional Layer is compacted and supplied to fully linked layer as its input.

For example, Neurons connected to nearby areas have their output computed in the first layer. A spot product of the weights and area is used to determine each. The usual sizes of filters used as inputs to images are 3, 5, or 8 square pixels. These filters learn the recurring patterns that appear anywhere in an image and then examine the entire image using a window sliding. The stride is distance between successive filters. If the step hyper parameter is less than filter dimension, the convolution is expanded to overlappable windows.

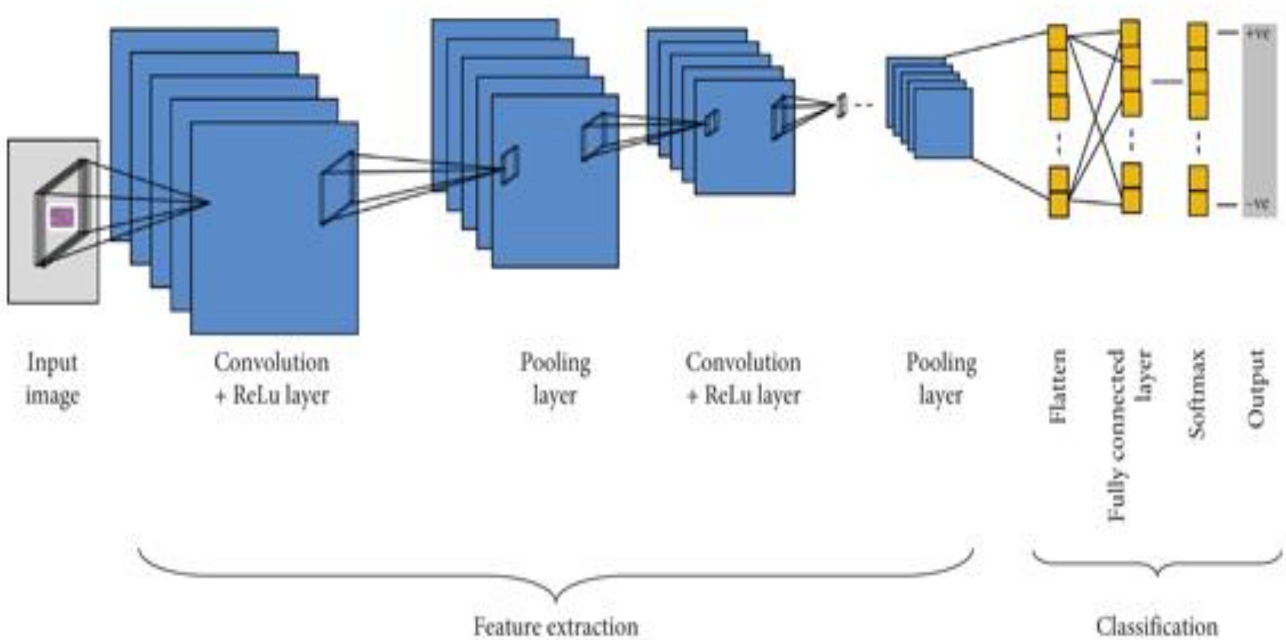

Figure 2: Typical Architecture of CNN (Google Courtesy)

The Figure 3 provides a visual description of Neural Networks (NN).

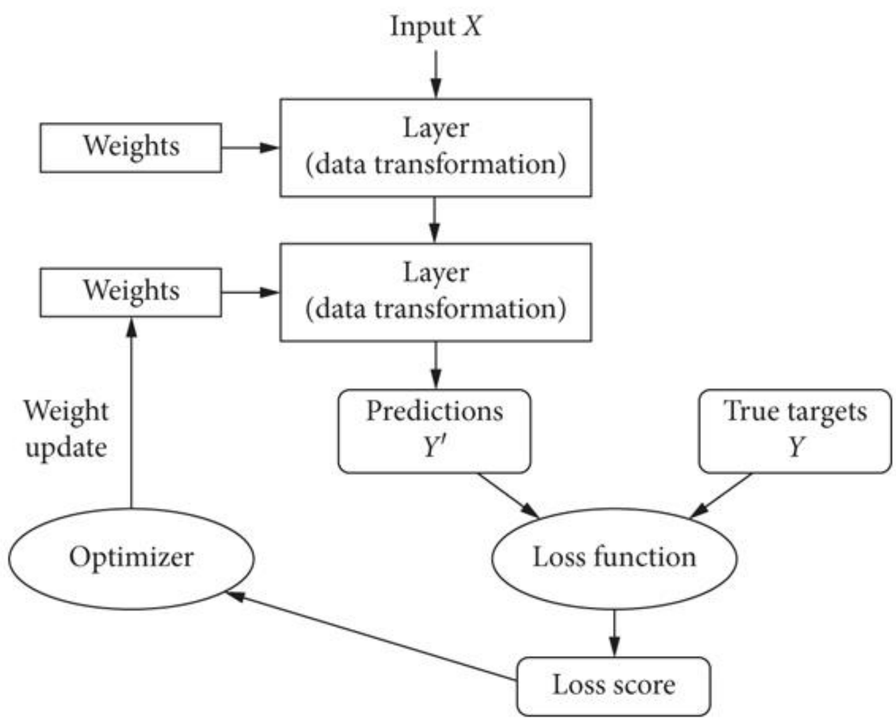

Figure 3: NN Workflow

4. EXPERIMENTAL ANALYSIS

Initially required packages scikit-learn functions like NumPy, seaborn, Pandas and matplotlib, frameworks have been installed in python for implementation. Then the RSNA Screening Mammography Breast Cancer dataset is uploaded and visualized the basic parameters as shown in Figure 4.

	site_id	patient_id	image_id	laterality	view	age	implant	machine_id	prediction_id
0	2	10008	736471439	L	MLO	81	0	21	10008_L
1	2	10008	1591370361	L	CC	81	0	21	10008_L
2	2	10008	68070693	R	MLO	81	0	21	10008_R
3	2	10008	361203119	R	CC	81	0	21	10008_R

	prediction_id	cancer
0	10008_L	0.021168
1	10008_R	0.021168

Figure 4: Visualizing Parameters of Data

Next the dataset images are in DICOM format so these are converted into JPEG images for easy open of the image. Because DICOM images loading will take more time. The JPEG format image are as displayed in Figure 5.

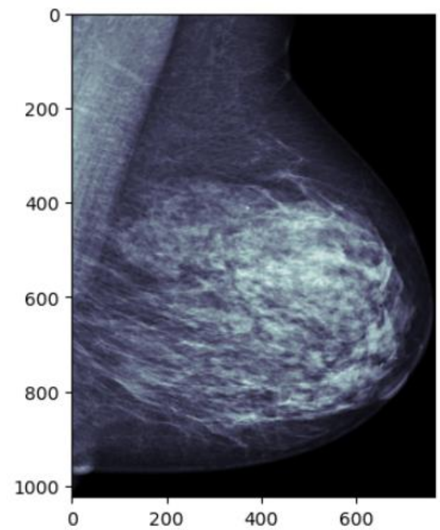

Figure 5: Breast Cancer Image after Converting DICOM to JPEG

By observing Figure 5, The images are in the form of RGB combination. So, three-dimensional arrays are used to store colour pictures. The image's height and breadth, in terms of pixels, make up the first two dimensions. The third dimension represents the pixel's red, green, and blue colour values. And for other uses in image analysis like predicting or finding objects in photographs. Then by using CNN model is pre-processed within 3 layers like: *Pooling Layer, Convolutional Layer, Fully-Connected layer*. First pre-processing of data is performed using CNN algorithm. Then model is defined and predicted the layer types with output shape parameters as shown in Figure 6.

```
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 image (InputLayer)             [(None, 1024, 768,   0           []
                                1)]

 tf.image.grayscale_to_rgb (TFO  (None, 1024, 768, 3  0          ['image[0][0]']
 pLambda)                       )

 tf.cast (TFOpLambda)           (None, 1024, 768, 3  0           ['tf.image.grayscale_to_rgb[0]
[0]
                                )                                '] 

 tf.math.truediv (TFOpLambda)   (None, 1024, 768, 3  0           ['tf.cast[0][0]']
                                )

 tf.math.subtract (TFOpLambda)  (None, 1024, 768, 3  0           ['tf.math.truediv[0][0]']
                                )

 convnext_v2_tiny (Functional)  (None, 32, 24, 768)  27864960    ['tf.math.subtract[0][0]']

 spatial_dropout2d (SpatialDrop  (None, 32, 24, 768)  0          ['convnext_v2_tiny[0][0]']
 out2D)

 global_average_pooling2d (Glob  (None, 768)         0           ['spatial_dropout2d[0][0]']
 alAveragePooling2D)

 dense (Dense)                  (None, 512)          393728      ['global_average_pooling2d[0]
[0]'
                                                                 ]

 dropout (Dropout)              (None, 512)          0           ['dense[0][0]']

 dense_1 (Dense)                (None, 256)          131328      ['dropout[0][0]']

 dropout_1 (Dropout)            (None, 256)          0           ['dense_1[0][0]']

 dense_2 (Dense)                (None, 128)          32896       ['dropout_1[0][0]']

 dropout_2 (Dropout)            (None, 128)          0           ['dense_2[0][0]']

 patient_id (InputLayer)        [(None, 1)]          0           []

 image_id (InputLayer)          [(None, 1)]          0           []

 dense_3 (Dense)                (None, 1)            129         ['dropout_2[0][0]']

==================================================================================================
Total params: 28,423,841
Trainable params: 0
Non-trainable params: 28,423,841
__________________________________________________________________________________________________
```

Figure 6: Prediction of Layer Types with Output Shape Parameters

In this stage the images with same type and shape (parallel) are combined for easy identification of BC tumors which is shown in Figure 7. In Figure 7, shows the parallel images that are combined for example L:9.8e-07, L:1.1e-06 and R:2.2e-06, R:2.8e-06 are same images but with some slight variations is combined for easy identification of tumor.

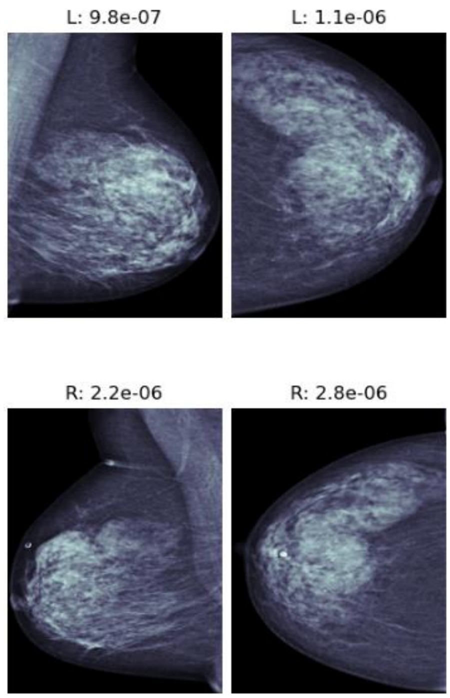

Figure 7: Parallel Image Processing

Later the models are trained on training images with 70% of training and 30% of testing or validation. Because when some of the testing images are overly similar to training images in the dataset cannot enter in different train or validation metrics. The resultant training and validation images are shown in Figure 8 and Figure 9.

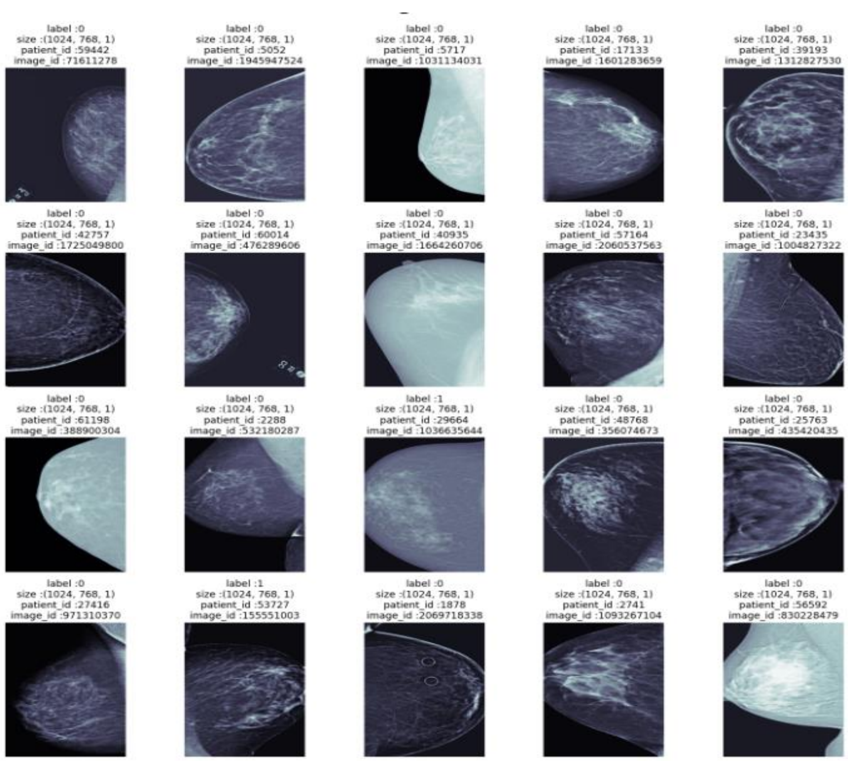

Figure 8: Training Images

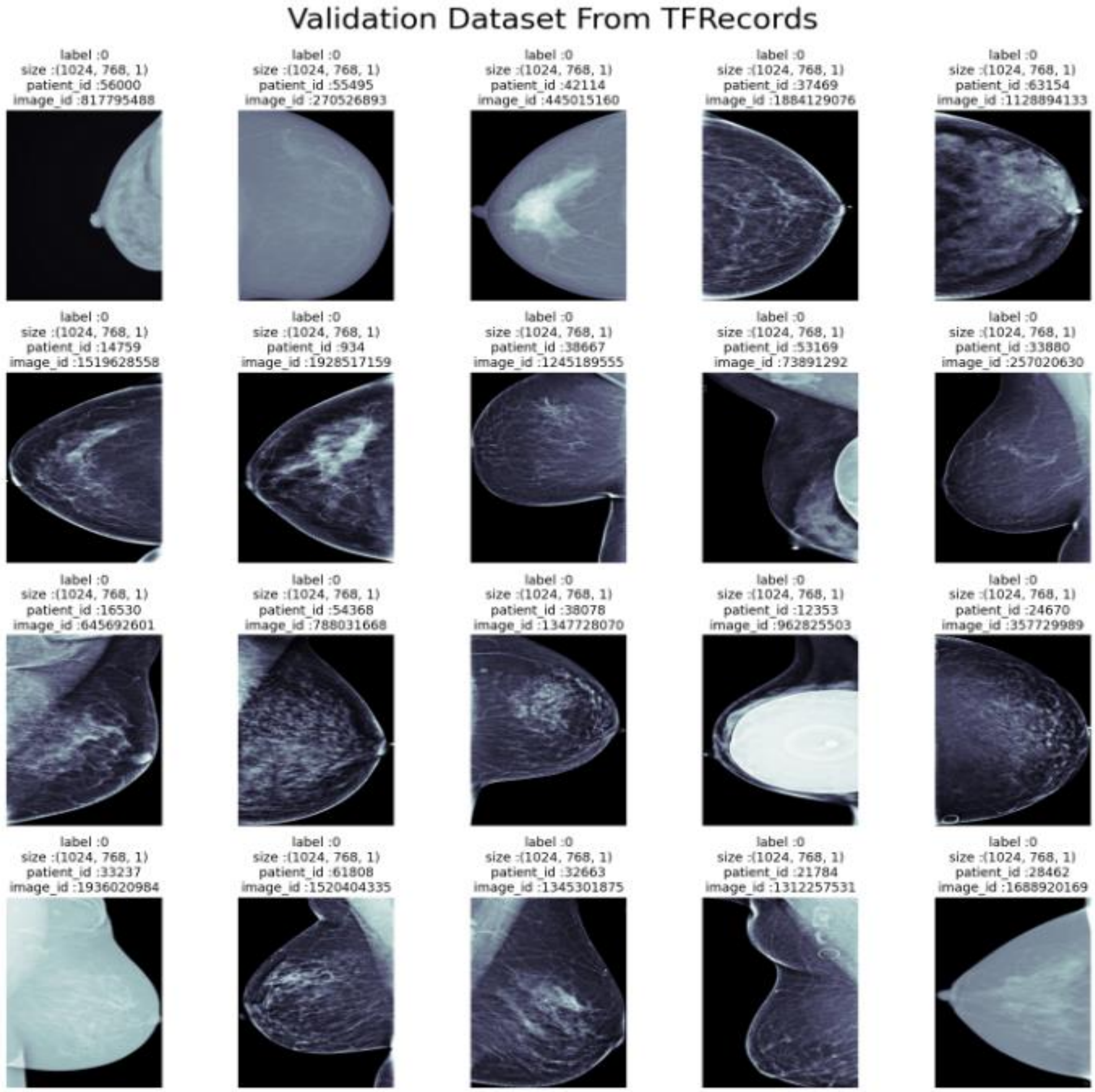

Figure 9: Validation Images

By observing the Figure 8 and 9 the breast cancer images in different angles and different sizes by using this training tumor is easily identified.

Then accuracy of CNN model after performing training and testing on data is shown in Table 1.

Table 1. Training and Testing Model Performance

Precision	Recall	F1-Score	Accuracy
98%	98%	98%	97%

As per table 1, CNN model has achieved an accuracy of 97%, whereas precision is 98%, recall is 98% and F1-score is 98%.

Then the training data is analysed to identify the tumor images based on the variable patient_id with x-axis as severity of the patient and y-axis as patient images count after parallel images are combined is shown in Figure 10.

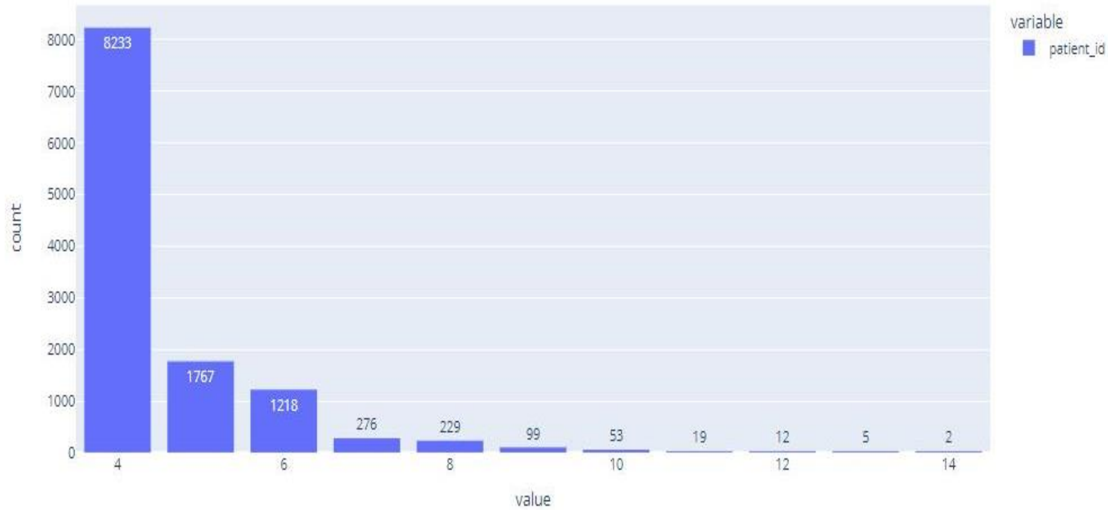

Figure 10: Visualization of Patients Images

By observing Figure 10 around 8233 images are tumor images and 1767 are normal images, 229 are severe diseased images and 2 are most critical images in the data.

Then the training data is also analysed for predicting breast cancer patients throughout world is shown in Figure 11.

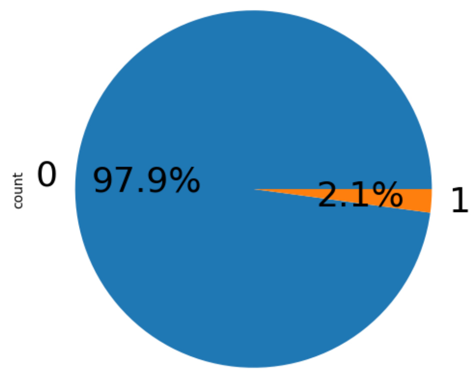

Figure 11: Pie Chart for Cancer Distribution

By observing Figure 11 it is clear that 97.9% of population are effected with breast cancer. Also, patients around 9,000 are having cancer and around 3,000 patients has invasive cancer i.e., in critical stage is visualised in Figure 12.

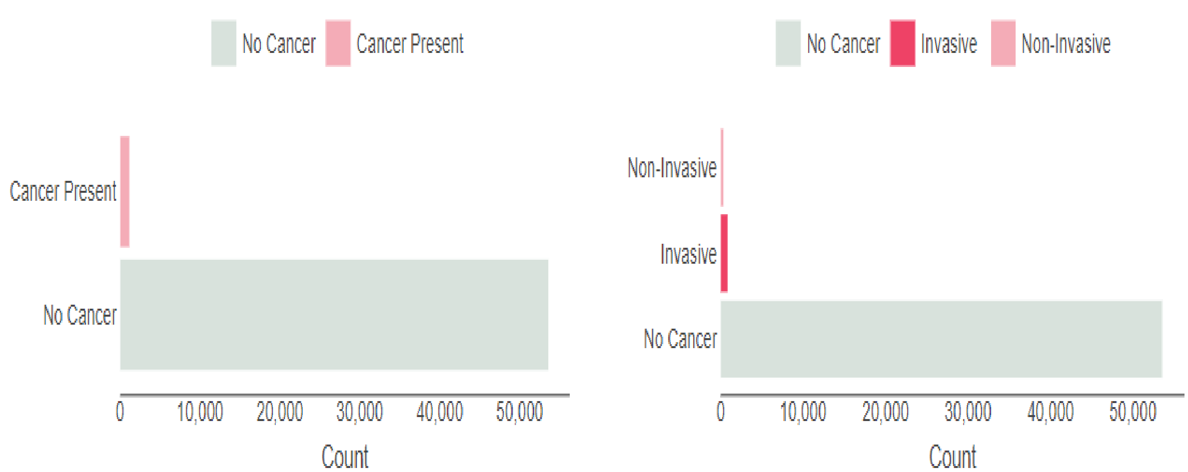

Figure 12: Patients with Cancer and No Cancer

By observing Figure 12, the x- axis with count of patient and y-axis is cancer patient severity are considered light pink color represents patients having cancer and dark pink color represents invasive patients i.e., means there are in critical stage and light green color represents no cancer. With the analysis of training data, it is also observed that around the age 50 to 70 age women are highly affected by breast cancer is visualised in Figure 13 by considering the variable as age, parameters X-axis as age values and Y-axis as age count.

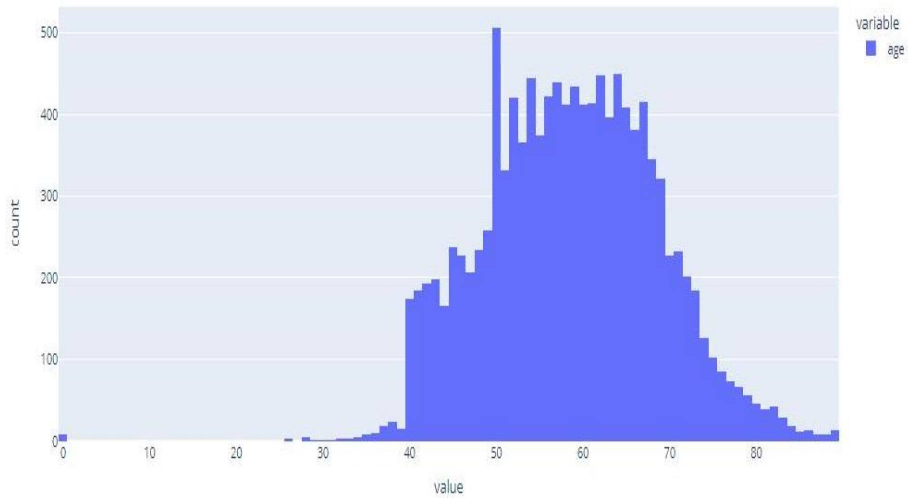

Figure 13: Distribution of Patients Age

Then analysed cancer status with the age on X-axis and age propotion on Y-axis as shown in Figure 14.

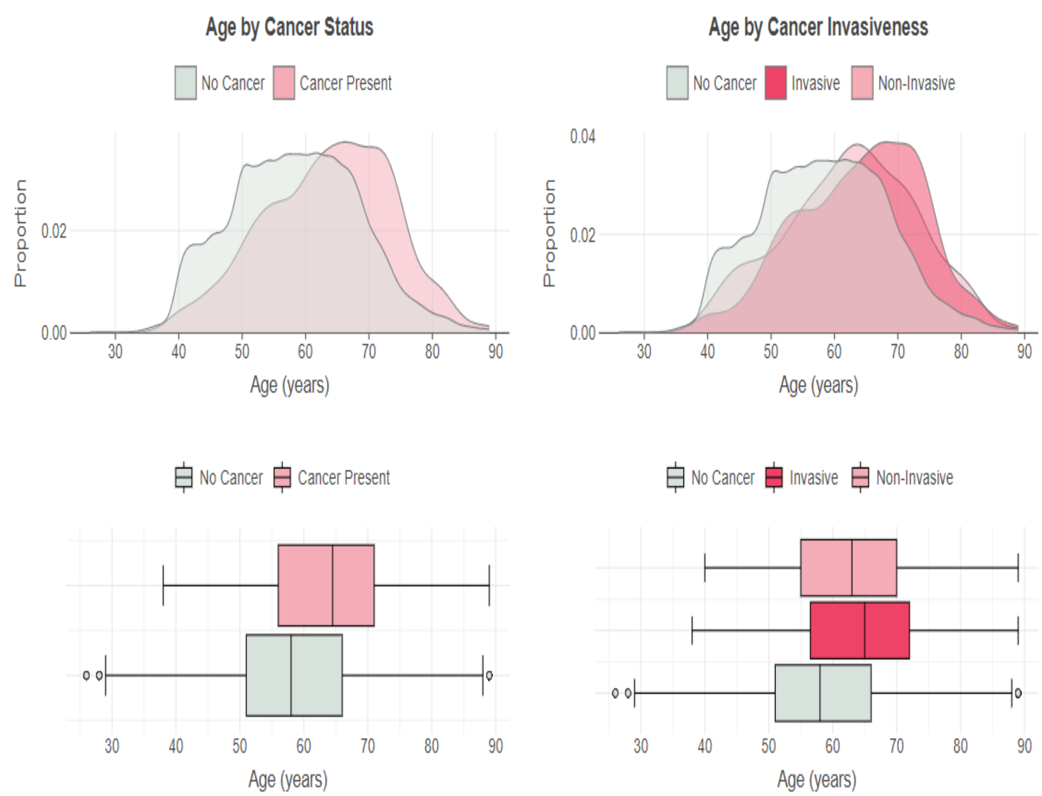

Figure 14: Cancer Status based on Ages

As Figure 14, The light pink color represents women around the age of 30 to 90 years are suffering with breast cancer whereas dark pink color represents woment around the age of 50 to 70 years are mostly in critical stage is visualised in Figure 14.

5. CONCLUSION

Breast cancer is one of the kind of cancer that begins in breast cells and is extremely prevalent in females. After lung cancer, BC is one of the lethal diseases in women may get. Breast cancer detection is a difficult endeavour with the goal of improving patient care. Since CNNs are another sort of neural network that discovers crucial data in both time series and picture data. So, by applying CNN on the 2023 RSNA (Radiological Society for North America) Screening Mammography Breast Cancer data predicted and analysed breast cancer using electronic cancer record and image data. Analysis depicts how best CNN algorithm is for identifying breast cancer with an accuracy of 97% and also tried to analyse at what age cancer is mostly occurred in women.

6. REFERENCES

[1] Hanahan D., Weinberg R.A. (2000) The Hallmarks of Cancer. *Cell.* 100:57–70. doi: 10.1016/S0092-8674(00)81683-9.

[2] Sung H., Ferlay J., Siegel R.L., Laversanne M., Soerjomataram I., Jemal A., Bray F. (2021), Global Cancer Statistics 2020: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries. *CA Cancer J. Clin,* 71:209–249. doi: 10.3322/caac.21660.

[3] Duggan C., Dvaladze A., Rositch A.F., Ginsburg O., Yip C., Horton S., Rodriguez R.C., Eniu A., Mutebi M., Bourque J., et al. (2020) The Breast Health Global Initiative 2018 Global Summit on Improving Breast Healthcare Through Resource-Stratified Phased Implementation: Methods and overview. *Cancer,* 126:2339–2352. doi: 10.1002/cncr.32891.

[4] World Health Organization. *Global Health Estimates 2016: Disease Burden by Cause, Age, Sex, by Country and by Region, 2000–2016.* World Health Organization; Geneva, Switzerland: 2018. [(accessed on 9 July 2021)]. Available online: https://www.who.int/healthinfo/global_burden_disease/esti-mates/en/index1.html

[5] Ferlay J., Ervik M., Lam F., Colombet M., Mery L., Piñeros M., Znaor A., Soerjomataram I., Bray F. (2020), *Global Cancer Obser-Vatory: Cancer Today.* International Agency for Research on Cancer; Lyon, France.

[6] DeSantis C.E., Fedewa S.A., Sauer A.G., Kramer J.L., Smith R.A., Jemal A. (2015), Breast cancer statistics, 2015: Convergence of incidence rates between black and white women. *CA A Cancer J. Clin,* 66:31–42. doi: 10.3322/caac.21320.

[7] Sharma R. (2021) Global, regional, national burden of breast cancer in 185 countries: Evidence from GLOBOCAN 2018. *Breast Cancer Res. Treat.*187:557–567. doi: 10.1007/s10549-020-06083-6.

[8] Ginsburg O., Bray F., Coleman M., Vanderpuye V., Eniu A., Kotha S.R., Sarker M., Huong T.T., Allemani C., Dvaladze A., et al. (2016) The global burden of women's cancers: A grand challenge in global health. *Lancet.* 389:847–860. doi: 10.1016/S0140-6736(16)31392-7.

[9] Vostakolaei F.A., Karim-Kos H.E., Janssen-Heijnen M.L.G., Visser O., Verbeek A.L.M., Kiemeney L. (2010) The validity of the mortality to incidence ratio as a proxy for site-specific cancer survival. *Eur. J. Public Health.* 21:573–577. doi: 10.1093/eurpub/ckq120.

[10] Sankaranarayanan R., Swaminathan R., Brenner H., Chen K., Chia K.S., Chen J.-G., Law S.C., Ahn Y.-O., Xiang Y.B., Yeole B.B., et al. (2010) Cancer survival in Africa, Asia, and Central America: A population-based study. *Lancet Oncol,* 11:165–173. doi: 10.1016/S1470-2045(09)70335-3.

[11] Sharma R. (2019) Breast cancer incidence, mortality and mortality-to-incidence ratio (MIR) are associated with human development, 1990–2016: Evidence from Global Burden of Disease Study 2016. *Breast Cancer,* 26:428–445. doi: 10.1007/s12282-018-00941-4.

[12] Masud M., Eldin Rashed A. E., Hossain M. S. (2020) Convolutional neural network-based models for diagnosis of breast cancer. *Neural Computing and Applications.* 5 doi: 10.1007/s00521-020-05394-5.

[13] Hossain M. S. (2017) Cloud-supported cyber-physical localization framework for patients monitoring. *IEEE Systems Journal,* 11(1):118–127. doi: 10.1109/jsyst.2015.2470644.

[14] Wahab N., Khan A. (2020) Multifaceted fused-CNN based scoring of breast cancer whole-slide histopathology images. *Applied Soft Computing,* 97: p. 106808. doi: 10.1016/j.asoc.2020.106808.

[15] Gravina M., Marrone S., Sansone M., Sansone C. (2021) DAE-CNN: exploiting and disentangling contrast agent effects for breast lesions classification in DCE-MRI. *Pattern Recognition Letters.*;145:67–73. doi: 10.1016/j.patrec.2021.01.023.

[16] Tsochatzidis L., Koutla P., Costaridou L., Pratikakis I. (2021) Integrating segmentation information into CNN for breast cancer diagnosis of mammographic masses. *Computer Methods and Programs in Biomedicine,* 200:p. 105913. doi: 10.1016/j.cmpb.2020.105913.

[17] Malathi M., Sinthia P., Farzana F., Aloy Anuja Mary G. (2021) Breast cancer detection using active contour and classification by deep belief network. *Materials Today: Proceedings.* doi: 10.1016/j.matpr.2020.11.551.

[18] Desai M., Shah M. (2021) An anatomization on breast cancer detection and diagnosis employing multi-layer perceptron neural network (MLP) and Convolutional neural network (CNN) *Clinical eHealth.* ; 4:1–11. doi: 10.1016/j.ceh.2020.11.002.

[19] Abdelhafiz D., Bi J., Ammar R., Yang C., Nabavi S. (2020) Convolutional neural network for automated mass segmentation in mammography. *BMC Bioinformatics.* ;21(1):1–19. doi: 10.1186/s12859-020-3521-y.

[20] Rezaeilouyeh H., Mollahosseini A., Mahoor M. H. (2016) Microscopic medical image classification framework via deep learning and shearlet transform. *Journal of Medical Imaging,* (4) doi: 10.1117/1.jmi.3.4.044501.044501

[21] Murtaza G., Shuib L., Abdul Wahab A. W., et al. (2020) Deep learning-based breast cancer classification through medical imaging modalities: state of the art and research challenges. *Artificial Intelligence Review,* 53(3):1655–1720. doi: 10.1007/s10462-019-09716-5.

[22] Alhamid M. F., Rawashdeh M., Al Osman H., Hossain M. S., El Saddik A. (2015) Towards context-sensitive collaborative media recommender system. *Multimedia Tools and Applications.,* 74(24):11399–11428. doi: 10.1007/s11042-014-2236-3.

[23] Qian S., Zhang T., Xu C., Hossain M. S. (2015) Social event classification via boosted multimodal supervised latent dirichlet allocation. *ACM Transactions on Multimedia Computing, Communications, and Applications,* 11(2):1–22. doi: 10.1145/2659521.

[24] Singh D., Singh S., Sonawane M., Batham R., Satpute P. A. (2017) Breast cancer detection using convolution neural network. *International Research Journal of Engineering and Technology,* 5(6):316–318.

[25] Kumar P., Srivastava S., Mishra R. K., Sai Y. P. (2020) End-to-end improved convolutional neural network model for breast cancer detection using mammographic data. *The Journal of Defense Modeling and Simulation: Applications, Methodology, Technology.* doi: 10.1177/1548512920973268.154851292097326

[26] Alhussein M., Muhammad G., Hossain M. S., Amin S. U. (2018) Cognitive IoT-cloud integration for smart healthcare: case study for epileptic seizure detection and monitoring. *Mobile Networks and Applications.* 23(6):1624–1635. doi: 10.1007/s11036-018-1113-0.

[27] Hossain M. S., Muhammad G., Guizani N. (2020) Explainable AI and mass surveillance system-based healthcare framework to combat COVID-I9 like pandemics. *IEEE Network,* 34(4):126–132. doi: 10.1109/mnet.011.2000458.

[28] https://www.rsna.org/education/ai-resources-and-training/ai-imagechallenge/screening-mammography-breast-cancer-detection-ai-challenge.

DOI: https://doi.org/10.15379/ijmst.v10i2.2775