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Breast cancer Prediction using Deep Learning Technique

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Abstract- Breast cancer is the second most frequent form of the disease, behind lung cancer. The most prevalent kind of cancer is that of the lung. Women of reproductive age are more likely to be diagnosed with breast cancer than men. Early detection of breast cancer is essential for reducing the death rate; this is due to the fact that the actual cause of breast cancer is unclear. Early detection of cancer may increase the likelihood of survival by up to 8%. This includes X-rays, mammograms, and even MRIs in certain cases. What's the matter even the most skilled radiologists have difficulty recognizing minute lumps, bumps, and masses, which results in a large number of false positives and false negatives? This is a really bad sign. A great number of people have the goal of creating more effective apps to diagnose breast cancer at an earlier stage. Photos may now be analyzed by new technology, which can then learn from the results. We used a Deep Convolutional Neural Network (CNN) in this investigation to differentiate between calcifications, masses, asymmetry, and carcinomas. Earlier studies made use of fundamental algorithms to accomplish this goal. The cancer was categorized as either benign or malignant, which made it possible to provide more effective treatment. An earlier training session had been completed for the model. To begin, we put this approach to use in order to successfully complete transfer learning. ResNet50. In a similar vein, we enhanced our model for deep learning. During the process of neural network training, the importance of its learning rate cannot be overstated. The learning rate may be adapted to changes using the method that we provide. When one is first being educated, they will make several mistakes.

Keywords- Breast Cancer, CNN, Mammograms-MINI-DDSM, Machine Learning.

I. INTRODUCTION

Breast cancer is the second most common disease in both men and women in the world, behind lung cancer, according to the World Health Organization. It was the cause of 12 percent of all new cancer cases in the year 2012. Female cancers accounted for 25 percent of all malignancies in 2012, according to the National Cancer Institute.

Breast cancer occurs as a consequence of unregulated cell proliferation occurring inside the breasts of women who are vulnerable to the disease. An x-ray image of a tumour or the sensation of a bulge on the body is the outcome of these cells cooperating to form a tumour. It is considered malignant when the tumor's cells are able to infiltrate (invade) and spread (metastasize) to other parts of the body (cancer).

These cells are derived from this source. Breast milk glands produce them. Good or bad, depending on how quickly the weird cells develop and what harm they inflict on other cells, these odd cells may be classed. In fact, the WHO estimates that approximately 2.1 million new instances of breast cancer occur each year in women all over the globe. In 2018, an estimated 627,000 women lost their lives to breast cancer, accounting for around 15% of all female cancer fatalities. 3–6 Machine learning has yet to be utilized to discover and categories breast tumours, despite a large body of work on the subject. Breast cancer is thought to be detectable when specific symptoms begin to occur.

As a result, it was discovered that many women with breast cancer did not exhibit any symptoms of the disease at all. When it comes to breast cancer prevention, those who have the BRCA1 or BRCA2 gene mutations are the only ones who can do so from the outset. On the other hand, treatments offered to cancer patients may influence their prognosis and likelihood of recurrence. Breast cancer patients often get a combination of surgical resection, chemotherapy, radiation therapy, and hormone therapy.

As a consequence, early detection of breast cancer is essential. In the early stages of cancer, lives may be saved. If breast cancer is discovered early, it may be identified and treated more swiftly. Because long-term survival is highly reliant on prognosis [7, 8], this information is crucial. A patient's chances of successfully receiving cancer therapy decrease as time passes without treatment.

Early detection and treatment for early-stage breast cancer symptoms may improve survival rates and slow or halt the growth of malignant cells, according to research by [9]. Many individuals are hopeful about the development of breast cancer detection and classification apps that function effectively because of advances in medical image processing. Computer algorithms are becoming more significant in the medical industry due to the usage of deep learning algorithms, which are able to recognize patterns since they employ layers of neural networks. Breast abnormalities may still be difficult to diagnose or categorise, despite extensive research towards automated breast cancer applications.

There's more. Aside from the lack of training data in the medical profession, deep learning also requires a large amount of training data. More research on apps that can automatically identify breast cancer is needed in the future. Deep learning models were utilized to identify whether abnormalities were genuine in this investigation. The following is a succinct summary of what this research has to offer: Using a pre-trained model called ResNet50, we devised strategies for preventing models from being overfit. In order to improve the performance of the deep CNN model, we tweaked its learning rate. We also looked for techniques to alter the pace of learning while training was taking place. Many of the factors that cause breast cancer and other ones that don't can be distinguished by our model.

II. RELATED WORK

Better mammography, which showed breast calcifications in the 1990s, led to the widespread use of CNN in clinical imaging. The usage of technology was a result of this. Pre-planned CNN relies heavily on the network's ability to respond to changing circumstances [24-32]. In clinical imaging, motion learning may be divided into two categories: Initial groups are used to identify the most critical qualities of a layer within an organisation. An additional categorization example like this one is then created using this layer. There are little structural changes in the second stage, save for the removal of entirely linked floors.

CNN illumination is just a few of the techniques that may be used to eliminate the dataset's bright spots. It was put to good use in a slew of investigations. Using a variety of different extraction classifiers and methods, for example, they examined a large number of images together.

Things were classified using the SIFT and the SVM [33-36]. One may find components that were both helpful and dangerous. It was critical to consider all three categories of constituents (child-heart, benign, and harmful). In order to improve the dataset, mammograms were employed. To see how the second dataset differed from the first, it compared it to the first. DCT (Discrete curve altering) was used to separate advanced mammography into four groups and subsequently to develop CNNs using SVM and softmax layers [36-38], like the ones displayed above, among other things The material in the IRMA knowledge base was the subject of this query. The DCT and CT were shown to have mean accuracy of 81.83 percent and 82.74 percent, respectively, throughout their research [6].

Several high- and low-pass lines are employed to convey the time/space signal. Depending on the signal, the wavelet is measured and moved in a different manner. Changes in the curvature make it possible to detect thin lines on wedges. A variety of mental processes, such as hypotheses and logical reasoning, are exemplified by fluffy reasoning. When a numerical representation is not accessible, techniques may be utilized to supplement it [3]. In contrast, if you want to create a fluffy framework model, you will have to constantly update and rebuild it in order to stay current. Neurofluffy thinking and precise frameworks may be found in the defects and assertions that assist individuals think about how things should be done. The multi-scale curve is the most accurate method of estimating size, with an accuracy rate of 98.59 percent.
In certain circumstances, other approaches, such as C-mean bunching.

There are times when alternative approaches outperform the division's expertise. Three-dimensional ultrasound pictures were utilized to locate and differentiate grassy and non-fatty tissues on the surface of the water. After the water shifted, this is what the surface area looked like. [9] By K-bunching, thermography of the breasts may one day be utilized to detect breast cancer. A shadow study of the hot spot is indicated in this scenario (the disease area). Research shows that an ultrasound might be used to remove tumours and their components from the body. To prevent the tumour from being mixed up with the rest of the body, several guidelines derived from the tumour split have been used. Various categories have been employed to examine the facts, and flexible thresholds have been discovered.

There were encouraging findings from the use of a thick area ID approach for measuring stretch and screening for various forms of breast cancer. A total of 32 distinct gradations of image quality have been examined. Changing the dyadic wavelet change may also help to enhance and reduce noise from mammograms [12].

For example, micro calcification and mass discrepancies may be achieved with this procedure. The DDSM and MINI data sets were described using a weighted misfortune. Keeping the locator from straying to a more desirable area was a primary goal of this strategy. Application: ESTD and Surface Examination were two methods examined as part of the audit that were found to emphasize the extraction of pictures from mammograms. Self-changing asset allocation networks have been

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proposed for a variety of applications, including breast cancer research and lead component inspection.

III. DATASET

CNN must excel at this if it wants to maintain its position as the premier news source. It requires a large amount of data to train its algorithms. The biggest publicly accessible internet dataset at the time was used for training and testing. In this investigation, we'll make use of mammograms obtained using the MINI-DDSM [15]. The amount of photographs utilized is as follows: This objective was achieved with the aid of 5358 people.

Each image is 1372 by 2340 pixels. As part of their research, roughly 2474 photos were taken of the cancerous cells, whereas about 1940 photos were taken of the healthy cells. The course materials for the class were created using a random split of the dataset. Only 20% of the money was used on CNN testing and evaluations, the rest were used for training. The photos were converted to grayscale before being exhibited.

Table 1. Dataset description.

		Class	
		Benign	malignant
Images	Training Samples (80%)	1940	2474
	Test Samples (20%)	420	524

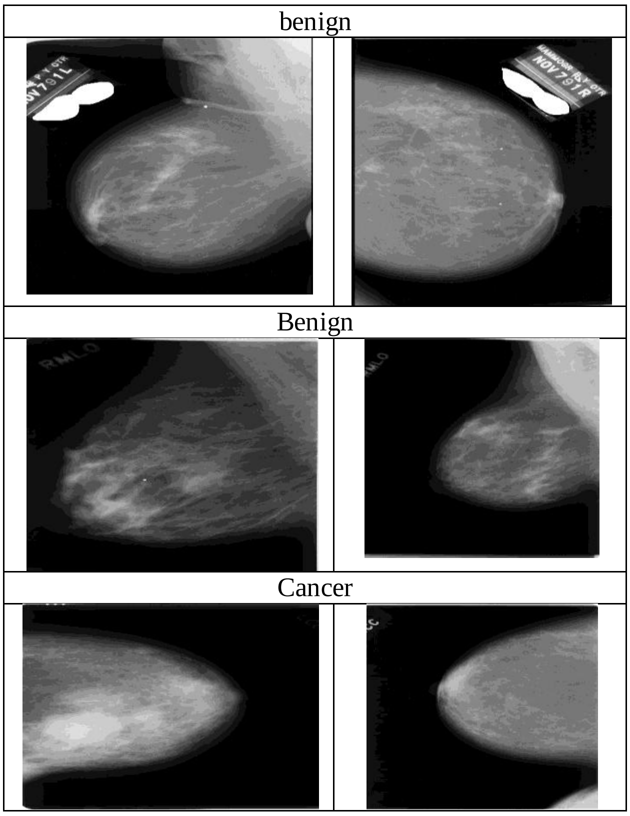

Fig 1. Images shows in working dataset.

IV. METHODOLOGY

The MINI-DDSM mammography pictures were used for training, and 80 percent of the 5,358 images were used for training. The technique for the suggested system is shown in Figure 2 (below).

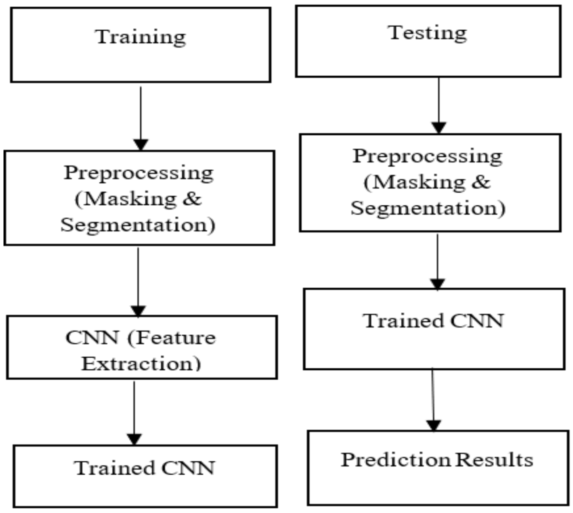

Fig 2. Shows working training and testing steps.

SGDM is practiced with stochastic downward momentum. In order to get the best results, we experimented with different learning rates, batch sizes, and durations. Table II provides an overview of some of the study's key metrics. An untrained CNN employee taught it from the ground up. Images may be analyzed using CNN algorithms that look for certain patterns or features. Big, conspicuous goods are sought for in the CNN's first stages. The preceding levels' more subtle characteristics must be uncovered by the next tiers. All of the attributes of the layers before it may be used to define the final layer.

Four convolutional layers are shown in Figure 3. The next three items, as shown in Figure 3, have no connection to one another. A grayscale version of the images is sent to CNN for use on the air. With a volume proportional to the area it covers, it generates a weighed point product. Four, 16, and 80 filters (2, 3, 5) and padding were used to make the input layer more visually appealing (3, 2, 1, 1). The filter shown by [3 3] has a height and breadth of three. The size of these filters is an issue. Filters must be repositioned so that they fit inside the input's width and height restrictions.

Two levels of bundling are employed to reduce time and boost the dependability of the system. Each area may include up to four inputs from layers with filter sizes ranging from two to two pixels. Two-pixel filter layers are utilized. Softmax Layer is a layer with a CNN classifier. Typically, this is the last layer to be applied. There will be more weight shifts for individuals that learn quicker at each level, and the network will progress more swiftly because of this. In actuality, the reverse is true. As you

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gain new knowledge, your weight fluctuates. A 0.001 study rate was used in our investigation.

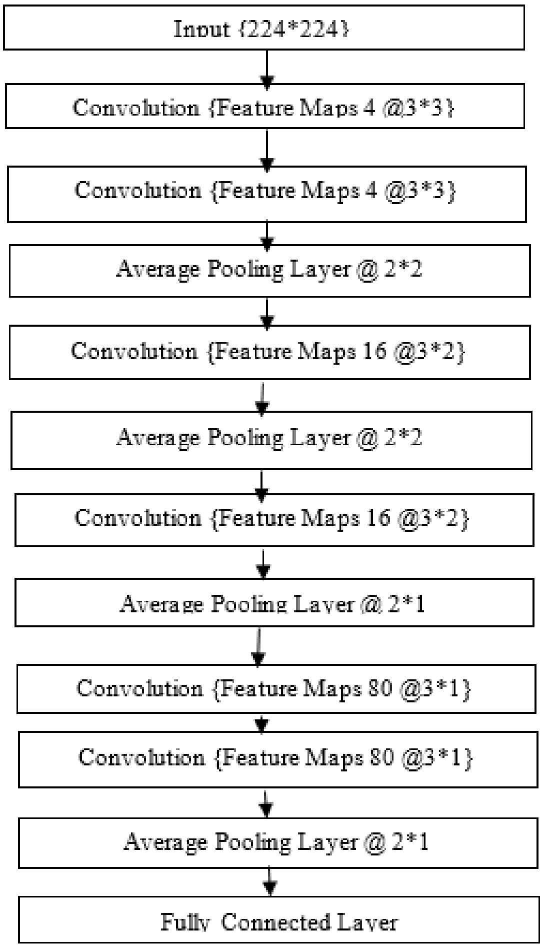

Fig 3. It's shown on the right.

The data utilized came from the creation and testing of CNNs. 1372 by 2340 pixels was the original size of the raw data when it was initially produced. 1940 and 2474, plus a few additional test photographs were divided into two groups. The two groups were separated. The physical and organic data sets of each preparation and test were analyses separately, resulting in varied conclusions. It is more effective to provide information that is relevant than to provide information that has been prepared. This approach yields a wealth of data about ribosomal disorders. It's seen in Fig. 6 how things went. Each new CNN edition and the usage of pre-made groups help to improve this long-term research.

It is best to start with a fresh set of CNN training and testing data. From 1372 by 2340 pixels to only 512 pixels, the photos were reduced in size by more than half. The photographs were shrunk in size as part of the collection's data collection procedure. How to binaries and hide the region of interest in order to learn more about it (ROIs). It is possible to utilize morphological techniques to reveal and conceal sections of images.

There were six groups with lovely photos of various cancers in them, whereas the seventh group had none. It was only a generalization of the other two. Bad or even lethal sights might be seen in these photographs. It is an assessment. There was no one who utilized any of the other one's three filter sizes (2, 3, 5). FIGURE 7: There was no issue with any of the filter sizes.

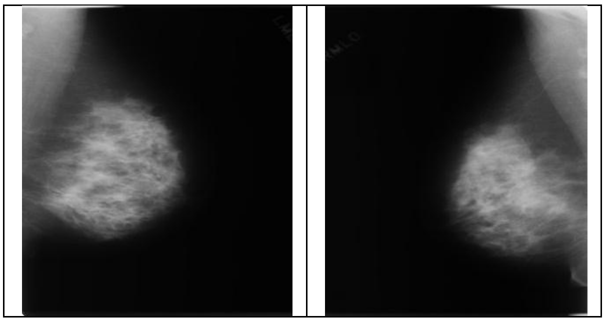

Fig 4. Experimental dataset images.

Input for the game came from real-world images. The last phase in the procedure was morphological closure. Anatomical closure resulted in dilatation, which in turn reduced noise. A trough disappears as soon as a minor hole is closed. Connected binary pictures had CC-related components, indicating that the images were linked. There were no obvious landmarks even in the most accessible part of town. Next, we used the masking technique shown in Figure 4. Figure 5 depicts this. It's possible to simplify the process of reading.

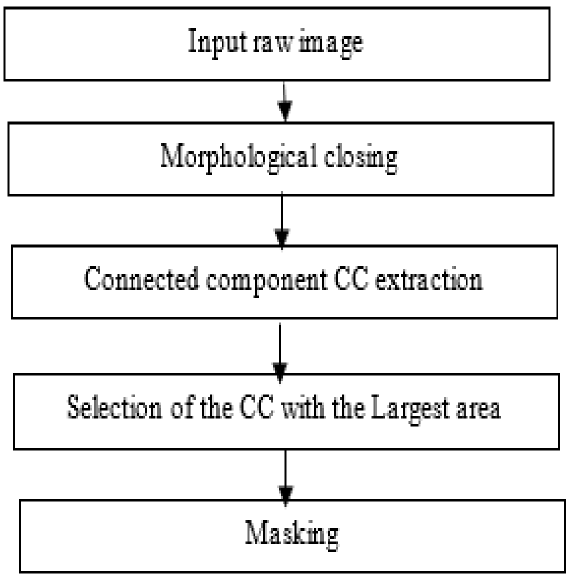

Fig 5. Pre-processing segmentation stages.

Platform Specs The implementation used Python language.

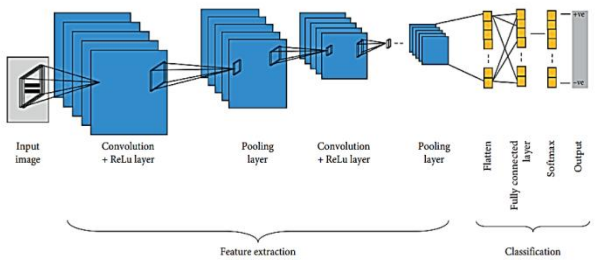

Fig 6. Feature extraction and clasification steps of CNN.

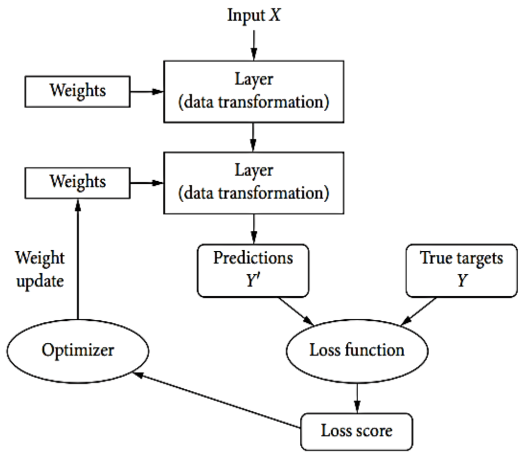

Fig 7. Working steps of NN

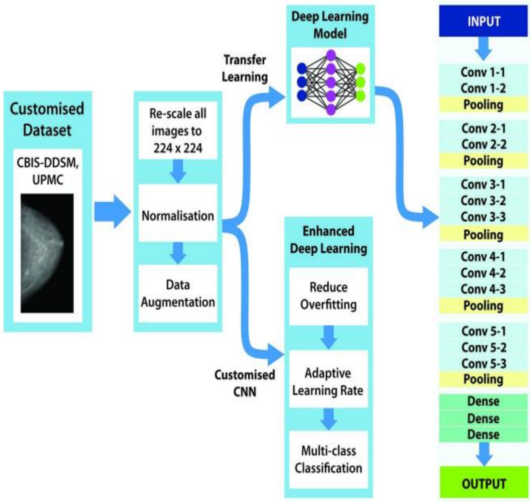

Fig 8. Proposed architecture.

V. RESULTS

There were seven primary categories and six subcategories in the early tests for breast cancer screening using a CNN. For both testing and training, there were two approaches available.. Data was initially divided between tumours that were benign and those that were malignant. Asymmetrical groups, calcification, spicy masses, confined masses, architectural deformation, variation, and calcification were the six forms of malignant groups discovered by the third technique.

A disorganized collection of pictures that may or may not be harmful. CNN used a collection of 2474 cancerous and 1940 healthy photos to train and test the algorithm. Applied to: Teaching the algorithm how to operate with the help of this data. Researchers employed both pre-processed and raw data in their study to train and evaluate their system. It's important pre-processing neural networks to boost their performance and speed of learning.

Depending on the CNN station you watch, you may see a variety of obscene visuals. Figure 9 demonstrates how near each image is to being correct. Our morphological procedures were employed to preserve this region as clean as feasible. Figure 4 illustrates this. Preprocessed data has greater appeal than unaltered images. That's what's seen in Figure 7: the MINI-DDSM dataset had an overall accuracy rating of 66%.

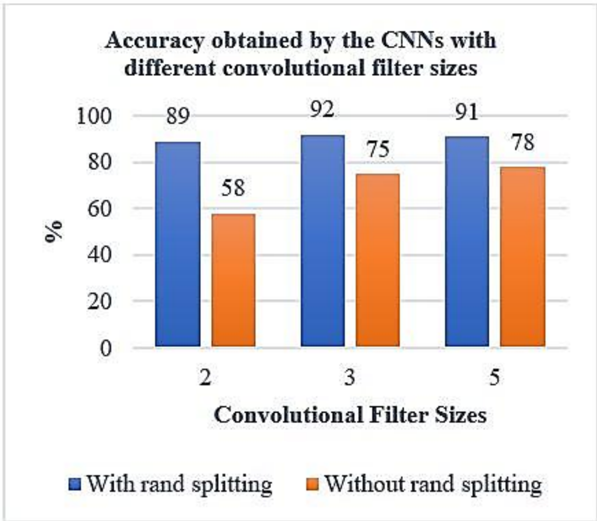

Fig 9. Accuracy of proposed method.

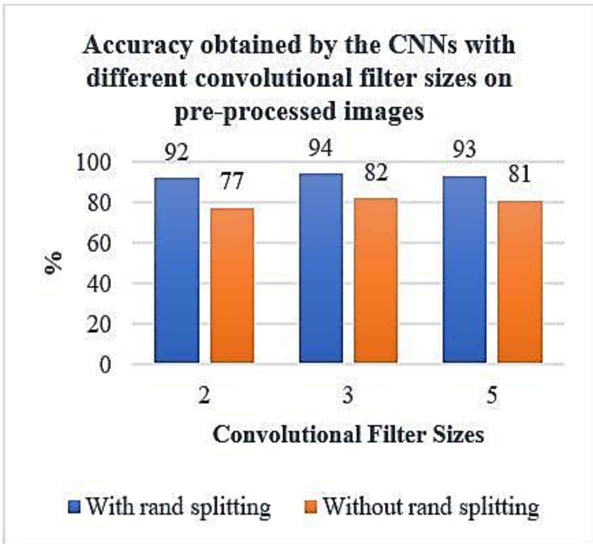

Fig 10. Accuracy of proposed method with pre processed images.

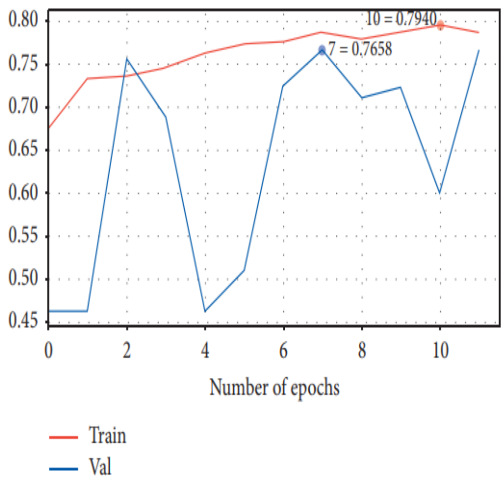

Fig 11. Number of epochs.

Table 2. Proposed models layers.

Layer	Type	Output shape	Param.
conv2d_2	Conv2D	None, 50, 50, 32	896
conv2d_3	Conv2D	None, 50, 50, 32	9248
max_pooling2d_1	MaxPooling2	None, 25, 25, 32	0
batch_normalization	BatchNo	None, 25, 25, 32	128
dropout_2	Dropout	None, 25, 25, 32	0
conv2d_4	Conv2D	None, 25, 25, 64	18496
conv2d_5	Conv2D	None, 25, 25, 64	36928
max_pooling2d_2	MaxPooling2	None, 12, 12, 64	0
batch_normalization_1	BatchNo	None, 12, 12, 64	256
dropout_3	Dropout	None, 12, 12, 64	0
conv2d_6	Conv2D	None, 12, 12, 86	49622
conv2d_7	Conv2D	None, 12, 12, 86	66650
max_pooling2d_3	MaxPooling2	None, 6, 6, 86	0
batch_normalization_2	Batch	None, 6, 6, 86	344
dropout_4	Dropout	None, 6, 6, 86	0
flatten_1	Flatten	None, 3096	0
dense_2	Dense	None, 512	1585664
dropout_5	Dropout	None, 512	0
dense_3	Dense	None, 2	1026
Total params.: 1,769,258			
Trainable params.: 1,768,894			
Nontrainable params.: 364			

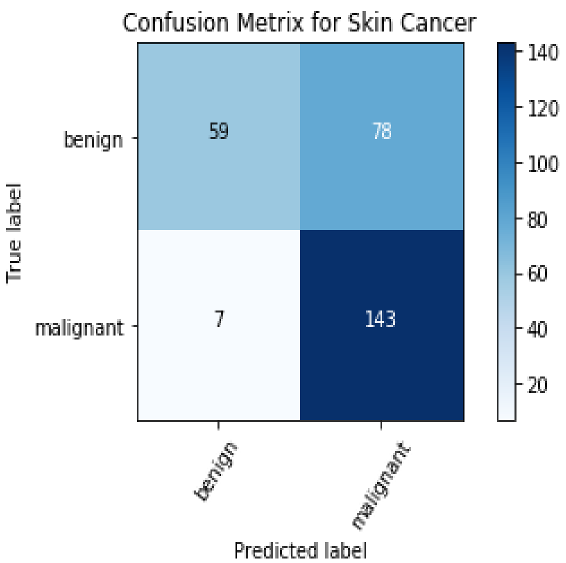

Fig 12. The confusion matrix of ProposedCNN Model.

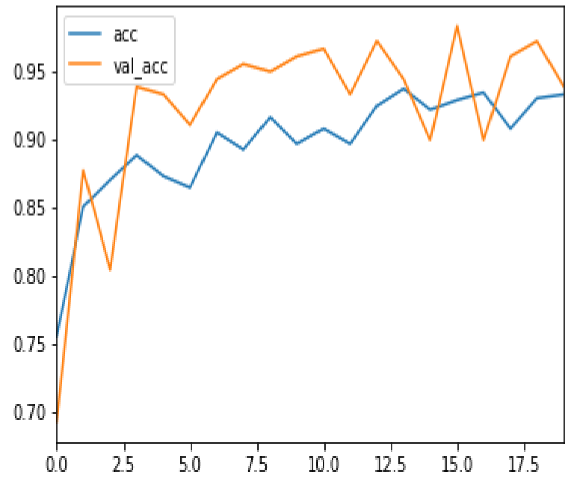

Fig 13. Accuracy and validate accuracy.

Table 3. Result in term of accuracy, precision; recall f1 score and Roc-Auc.

Accuracy	Precision	Recall	F1 Score	ROC-AUC
97..6%	68%	94%	79%	0.712

VI. CONCLUSION

In order to determine which mammograms were normal and which were not, researchers used convolutional neural networks. With the MINI-DDSM mammography dataset, proposed deep learning system able to categorize breast cancer. To increase the network's accuracy while dealing with raw data, a variety of filter sizes and preprocessing processes were used. When attempting to extract and categories properties from a dataset, accurate segmentation is essential. Masking and morphological segmentation greatly improved the classification of the images.

REFERENCE

[1] "Breast cancer statistics." [Online]. Available: http://www.wcrf.org/int/ cancer-facts-figures/data-specific-cancers/breast-cancer-statistics

[2] "Over 40,000 die of breast cancer every year in pakistan." [Online]. Available: http://www.google.com.pk/amp/s/www.dawn.com/news/amp/ 1319675

[3] S. Bagchi and A. Huong, "Signal processing techniques and computer-aided detection systems for diagnosis of breast cancer–a review paper," Indian Journal of Science and Technology, vol. 10, no. 3, 2017.

[4] F. A. Jaffer and R. Weissleder, "Molecular imaging in the clinical arena," Jama, vol. 293, no. 7, 2005.

[5] S. Liu, S. Liu, W. Cai, S. Pujol, R. Kikinis, and D. Feng, "Early diagnosis of alzheimer's disease with deep learning," IEEE, 2014

[6] J. C. Tobias Charistian Cahoon, Melanie A. Sutton, “Three-class mammogram classification based on descriptive cnn features,” 2000.
[7] S. Sharma, M. Kharbanda, and G. Kaushal, “Brain tumor and breast cancer detection using medical images,” International Journal of Engi-neering Technology Science and Research, vol. 2, 2015.
[8] P. Gu, W.-M. Lee, M. A. Roubidoux, J. Yuan, X. Wang, and P. L. Carson, “Automated 3d ultrasound image segmentation to aid breast cancer image interpretation,” Ultrasonics, vol. 65, 2016.
[9] P. Hankare, K. Shah, D. Nair, and D. Nair, “Breast cancer detection using thermography,” Int. Res. J. Eng. Technol, vol. 4, 2016.
[10] W. K. Moon, I.-L. Chen, J. M. Chang, S. U. Shin, C.-M. Lo, and R.-F. Chang, “The adaptive computer-aided diagnosis system based on tumor sizes for the classification of breast tumors detected at screening ultrasound,” Ultrasonics, vol. 76, 2017.
[11] F. Strand, K. Humphreys, A. Cheddad, S. Törnberg, E. Azavedo, J. Shepherd, P. Hall, and K. Czene, “Novel mammographic image features differentiate between interval and screen-detected breast cancer: a case-case study,” Breast Cancer Research, vol. 18, no. 1, 2016.
[12] A. Mencattini, M. Salmeri, R. Lojacono, M. Frigerio, and F. Caselli, “Mammographic images enhancement and denoising for breast cancer detection using dyadic wavelet processing,” IEEE transactions on instrumentation and measurement, vol. 57, no. 7, 2008.
[13] S. Hwang and H.-E. Kim, “Self-transfer learning for fully weakly supervised object localization,” arXiv preprint arXiv:1602.01625, 2016.
[14] Z. Mohammadzadeh, R. Safdari, M. Ghazisaeidi, S. Davoodi, and Z. Azadmanjir, “Advances in optimal detection of cancer by image processing; experience with lung and breast cancers,” Asian Pacific journal of cancer prevention: APJCP, vol. 16, no. 14, 2015.
[15] “Mammographic image analysis society digital mammogram database.” [Online]. Available: http://peipa.essex.ac.uk/info/MINI-DDSM.html
[16] M. M. Jadoon, Q. Zhang, I. U. Haq, S. Butt, and A. Jadoon, “Threeclass mammogram classification based on descriptive cnn features,” BioMed research international, 2017.
[17] “Breast cancer facts & figures 2017-2018.” [Online]. Available: https://www.cancer.org/content/dam /cancer-org/research/cancer-facts-and-statistics/breast-cancer-facts-and-figures/ breast-cancer-facts-and-figures-2017-2018.pdf
[18] K. Vennila, K. Sivakami, and R. Padmapriya, “Detection of mass in digital mammograms,” International Journal of Computer Applications, vol. 104, no. 5, 2014.
[19] K. Djaroudib, A. T. Ahmed, and A. Zidani, “Textural approach for mass malignantity segmentation in mammographic images,” arXiv preprint arXiv: 1412.1506, 2014.
[20] S. Deepa and V. S. Bharathi, “Efficient roi segmentation of digital mammogram images using otsu’s n thresholding method,” Indian Journal of Automation and Artificial Intelligence, vol. 1, no. 2, pp. 51–56, 2013.
[21] “Filters in the context of convolutional neural networks.” [Online]. Available: https://www.qu ora.com/ What-is-afilter-in-the-context-of-Convolutional-Neural-Networks
[22] T. P. K. Derek C. Rose, Itamar Arel and V. C. Paquit, “Applying deeplayered clustering to mammography image analytics,” 2010.
[23] B. R. Spandana Paramkusham*, Kunda.M.M. Rao**, “Early-stage detection of breast cancer using novel image processing techniques, matlab and labview implementation,” 2013.
[24] T. I. A. L. C. Muzni Sahar, Hanung Adi Nugroho, “Automated detection of breast cancer lesions using adaptive thresholding and morphological operation,” 2016.
[25] A. Taiwade, N. Gupta, R. Tiwari, S. Kumar and U. Singh, "Hierarchical K-Means Clustering Method for Friend Recommendation System," 2022 International Conference on Inventive Computation Technologies (ICICT), 2022, pp. 89-95, doi: 10.1109/ICICT54344.2022.9850852.
[26] R. Baghel, P. Pahadiya and U. Singh, "Human Face Mask Identification using Deep Learning with OpenCV Techniques," 2022 7th International Conference on Communication and Electronics Systems (ICCES), 2022, pp. 1051-1057, doi: 10.1109/ICCES54183.2022.9835884.
[27] M. Ranjan, A. Shukla, K. Soni, S. Varma, M. Kuliha and U. Singh, "Cancer Prediction Using Random Forest and Deep Learning Techniques," 2022 IEEE 11th International Conference on Communication Systems and Network Technologies (CSNT), 2022, pp. 227-231, doi: 10.1109/CSNT54456.20 22.9787608.
[28] Singh, Upendra, Gupta, Puja, and Shukla, Mukul. ‘Activity Detection and Counting People Using Mask-RCNN with Bidirectional ConvLSTM’. 1 Jan. 2022 : 6505 – 6520.
[29] Gupta, P., Shukla, M., Arya, N., Singh, U., Mishra, K. (2022). Let the Blind See: An AIIoT-Based Device for Real-Time Object Recognition with the Voice Conversion. In: Al-Turjman, F., Nayyar, A. (eds) Machine Learning for Critical Internet of Medical Things. Springer, Cham. https://doi.org/10.1007/978-3-030-80928-7_8
[30] Patidar, M., Singh, U., Shukla, S.K. et al. An ultra-area-efficient ALU design in QCA technology using synchronized clock zone scheme. J Supercomput (2022). https://doi.org/10.1007/s11227-022-05012-2
[31] A. Taiwade, N. Gupta, R. Tiwari, S. Kumar and U. Singh, "Hierarchical K-Means Clustering Method for

Friend Recommendation System," 2022 International Conference on Inventive Computation Technologies (ICICT), 2022, pp. 89-95, doi: 10.1109/ICICT543 44.2022.9850852.

[32] Jindal, R, Kumar, N, Patidar, S. IoT streamed data handling model using delta encoding. Int J Commun Syst. 2022; 35(13):e5243. doi:10.1002/dac.5243.

[33] S. Patidar, A. Jain and A. Gupta, "Comparative Analysis of Machine Learning Algorithms for Heart Disease Predictions," 2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS), 2022, pp. 1340-1344, doi: 10.1109/ICICCS53718.2022.9788408.

[34] B. Jain, S. Patidar and D. Sudershan, "Heterogeneous Software Defect Prediction using Generative Models," 2022 IEEE 11th International Conference on Communication Systems and Network Technologies (CSNT), 2022, pp. 367-372, doi: 10.1109/CSNT54 456.20 22.9787607.

[35] Singh, Shani Pratap and Shukla, Jayesh and Sharma, Shaili and Daga, khushhal and Bhalavi, Brahman Singh and Singh, Upendra, Face Mask Detection using Multi-Stage CNN Architecture (July 10, 2021). Proceedings of the International Conference on IoT Based Control Networks & Intelligent Systems - ICICNIS 2021, Available at SSRN: https://ssrn.com /abstract=3884022 or http://dx.doi.org/10. 2139/s srn.3884022

[36] Saxena, A. Vyas, L. Parashar and U. Singh, "A Glaucoma Detection using Convolutional Neural Network," 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2020, pp. 815-820, doi: 10.1109/ICESC48915.2020.9155930.

[37] Bamne, N. Shrivastava, L. Parashar and U. Singh, "Transfer learning-based Object Detection by using Convolutional Neural Networks," 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2020, pp. 328-332, doi: 10.1109/ICESC48915.20 20.9156060.

[38] Gupta, P., Shukla, M., Arya, N., Singh, U., Mishra, K. (2022). Let the Blind See: An AIIoT-Based Device for Real-Time Object Recognition with the Voice Conversion. In: Al-Turjman, F., Nayyar, A. (eds) Machine Learning for Critical Internet of Medical Things. Springer, Cham. https://doi.org/10.1007/978-3-030-80928-7_8

[39] Patidar, M., Singh, U., Shukla, S.K. et al. An ultra-area-efficient ALU design in QCA technology using synchronized clock zone scheme. J Supercomput (2022). https://doi.org/10.1007/s11227-022-05012-2