BREAST CANCER PREDICTING USING DEEPLEARNING WITH ARTIFICAL INTELLIGENCE

Mrs. Nandhini A[1], Mythili K[2]

[1]Assistant Professor (SG), Department of Computer Applications, Nehru college of management,Coimbatore, Tamilnadu, India.

[2] II MCA, Department of Computer Applications, Nehru college of management,Coimbatore, Tamilnadu, India.

Abstract: *Among women with cancer, breast cancer is the primary cause of death. Computer-aided diagnosis is a useful tool that helps doctors make early diagnoses and increases patientchances of recovery. Because the medical industry is so sensitive, it is imperative that artificial intelligence (AI) be used there. This indicates that a major problem is the classification algorithms' low accuracy in cancer detection. This issue is particularly noticeable in cases of fuzzy mammography images. The traditional convolutional neural network (TCNN) andsupported convolutional neural network (SCNN) methodologies are presented in this research using convolutional neural networks (CNNs). The TCNN and SCNN techniques provide a contribution by resolving the scale and shift issues that cause mammography pictures to become fuzzy. Furthermore, the flipped rotation-based method.*

Keywords: Breast cancer, cancer detection, mammography, convolutional neural network (CNN), traditional convolutional neural network (TCNN), supported convolutional neural network (SCNN).

1. Introduction:

There are numerous advantages of using artificial intelligence (AI) in the medical field. The rationale is that artificial intelligence (AI) is an automated process that robots may carry out on behalf of users (i.e. doctors, nurses, or medical professionals in the medical sector). AI's ability to reduce treatment costs and increase survival rates is another advantage for the medical field. In this case, early identification of breast cancer is a great illustration to back up this claim. Tiers of governmental medical facilities. For this reason, computer science researchers have used AI, and numerous strategies have been put forth, including. However, the accuracy of any suggested method for detecting breast cancer iswhat determines how good it is. Tiers of governmental medical facilities. For this reason, computer science researchers have used AI, and numerous strategies including have been put forth. However, the accuracy of any suggested method for detecting breast cancer iswhat determines how good it is.

State differently, a high error rate is critical andcan result in mortality in the medical area because of the sensitivity It is important to notethat this issue affects the majority of the works assessed in the related work section. diagnosis. When it comes to AI, the false positive (FP) cases that
the intelligent computer is unable to accuratelyclassify represent the mistake rate.

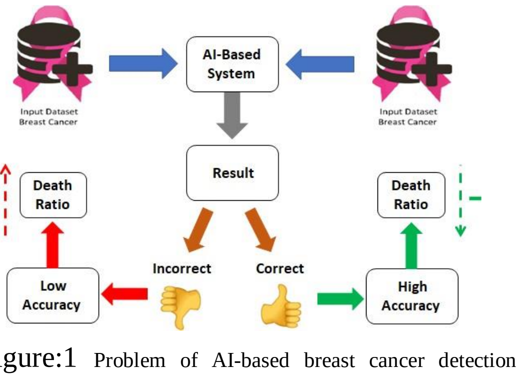

Figure:1 Problem of AI-based breast cancer detection systems.

Accuracy can be improved, and past questions can be addressed with the use of conventional neural networks (CNNs). This is so that, while the scaling problem can be handled by pooling functions, we can take advantage of the CNN's architecture to control the shifting problem based on traditional layers.

In general, the contributions of this works can be listed as follows:

- The CNN technique's design is utilized to address the shift issue brought on by blurring in mammography pictures. The suggested Traditional convolution neural network (TCNN) uses the padding technique to get around this issue.
- The CNN technique's design is utilized to address the scaling issue brought on by blurring in mammography images. To solve this issue, the max function in the suggested supported convolution neural network (SCNN) is utilized to build the pooling layers.
- In order to improve the classification process' accuracy, the flipped rotation-based approach (FRBA) is presented. In-depth tests are carried out to demonstrate the efficacy of the suggested techniques and evaluate them against analogous strategies.
- To demonstrate the efficiency of the suggested procedures and to compare them with other approaches of a similar nature, extensive experiments arecarried out.

Numerous solutions to the issue at handhave been provided by the latest study on these kinds of models. The answer to breastcancer prediction has only been found in a few weeks.

2. Related Work:

This section gives some background information on the field in which we operate and then reviews some of the methods that have been previously put forth under the general heading of artificial intelligence in the field of breast cancer detection research.

2.1. Background:

Context As seen in Figure 2, the intersection of four major disciplines can be used to illustrate the AI domain that deals with breast cancer diagnosis.

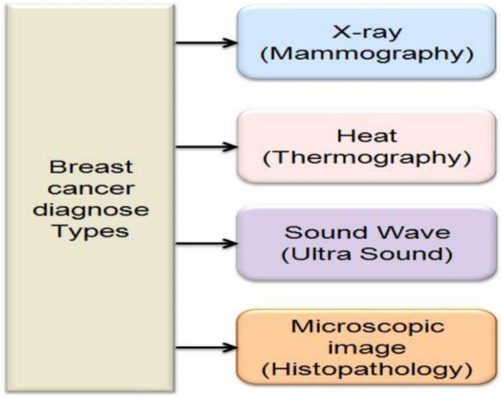

Figure:2 breast cancer diagnosis.

Figure 2 illustrates how disciplines like artificial intelligence (AI), x-ray, heat, sound wave, and microscopic imaging (MI) are all involved in the field of breast cancer diagnosis research. The science that investigates the possibility of giving machines the capacity to make decisions on behalf of people is known as artificial intelligence (AI). X-ray An X-ray image of the breast that can be used to identify breast cancer is called a mammogram. warmth A thermography system, which measures temperature variations in breast tissue using an infrared camera, can identify breast cancer. Regarding MI, it is an industry that offers products and services to patients in need of palliative, preventative, rehabilitative, and curative care.

2.2. Taxonomy of AI-based approaches for breast cancer diagnosis:

Numerous attempts, including [6], have been undertaken to classify AI-based systems for the detection of breast cancer. The explanation of feature extraction and selection processes, picture classification results, measurement parameterizations for classification, and approaches for classifying images related to breast cancer may be found in Ref [6]. Furthermore, it analyses three primary techniques: support vector machines (SVM), random forests (RF), and CNN. The authors of [33] present four popular architectures used for cancer detection and diagnosis: CNN, fully convolutional networks (FCNs), auto-encoders(AEs), and deep belief networks (DBNs). They also present classification from a medical point of view (i.e., relying on types of cancer). Through the presentation of a systematic review, the authors of [34] hope to shed light onthe current state of the art with regard to computer-aided diagnosis/detection (CAD) systems for breast cancer. The well-presented databases that are available for conducting tests for the diagnosis of breast cancer are what distinguish this work. Regarding benefits and drawbacks, [35] provides an overview of several different methods used in breast cancer screening. Furthermore, an investigation and analysis are conducted on the reviewed methodologies' performance.

Based on the two primary groups employed in this field of study, we categorize the methods for detecting breast cancer in the field of artificial intelligence. The stage 1 and stage 2 groups are depicted in Figure 3, with each group having its own methods or algorithms.

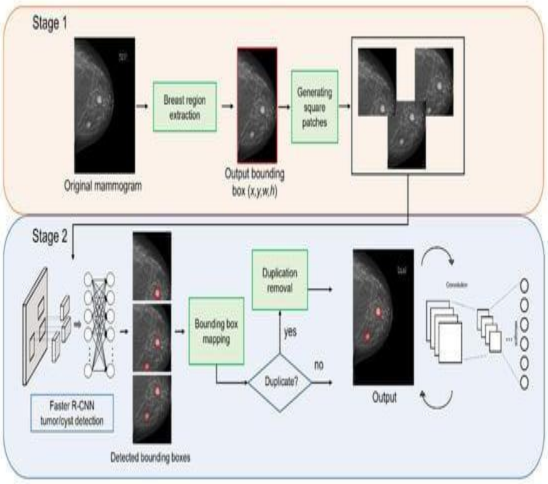

Figure:3 Related work AI-based systems.

3. Methodology:

In this work, we propose two approaches for breast cancer detection, illustrating the impact of image processing on the accuracy of the classification process. The first approach is called the traditional CNN (TCNN)-based approach. The second is called the supported CNN (SCNN)-based approach. Both the TCNN and SCNN approaches follow the same steps shown in Figure 4.

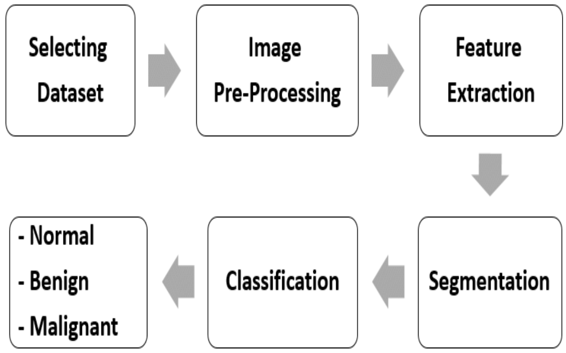

Figure:4 Flowchart of the methodology proposed approaches.

The suggested methodologies consist of six steps, as seen in Figure 4, which begin with dataset selection and end with the output (i.e., the kind of breast cancer). It is important to note that step 2 (image pre-processing) highlights the distinction between TCNN and SCNN.

The systems that put the suggested methodsinto practice typically have an input and an output. A mammography image is the input, and one of the three forms of cancer benign, malignant, or normal is the output. From amathematical perspective, the collection of cancer types is represented by the term "input image," which also refers to the system's output(classifier).

3.1. Selecting the Dataset:

University of Essex, MIAS (Mammographic Image Analysis Society) Dataset was used. **Description:** Includes labels for anomalies such as calcifications, confined masses, and spiculated lesions along with mammography images.

Use: Applied to image analysis for mammography-based breast cancer detection. **Size:**322 pictures illustrating various abnormality classes were used in the paper. **Link:** MIAS can provide it upon request.

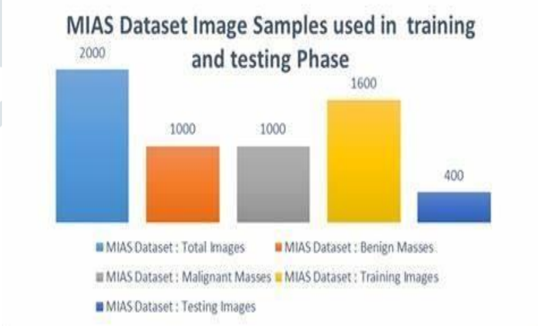

Table1: MIAS Dataset.

3.2. Image Pre-processing:

Improving the mammography images' quality is the aim of this step. Increased categorization accuracy follows from this. The rationale for this is that a diagnosis may be made with more accuracy the more distinct the borders and features are, which in turn increases the capacity to identify the tumour's location.

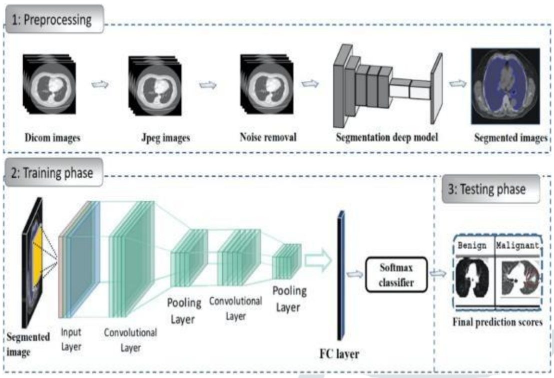

Figure:5 Details of the pre-processing step for both the TCNN and SCNN approaches.

3.3. Feature Extraction:

The following is a list of the general benefits of feature extraction techniques: 1.Accuracy improvements were made for the data.
2.Risk reduction from overfitting was done. 3.Quickening of instructions were made. 4.Better representation of the data were analysed.
5. Improvement In our model's explainability. Feature extraction in the CNN architecture isaccomplished by the formation of traditionallayers. In detail, a specific kernel (filter) scansthe mammography input image to create theconventional layers. CNN's architecture and thegeneral technique that creates conventionallayers are shown in Figure 6.

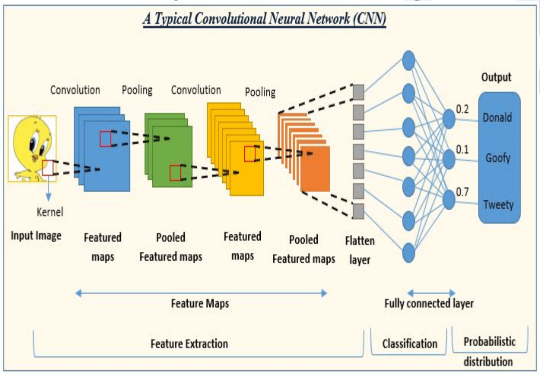

Figure:6 Convolutional Neural Network works.

3.4. Segmentation

The process of locating and separating the region of interest, such as a tumor, from medical imaging data (such as mammograms, MRIs, or ultrasound images) is known as segmentation in the context of breast cancer. By precisely defining the boundaries, size, and location of the tumor, segmentation serves as a tool for accurate breast cancer identification, classification, and treatment planning.

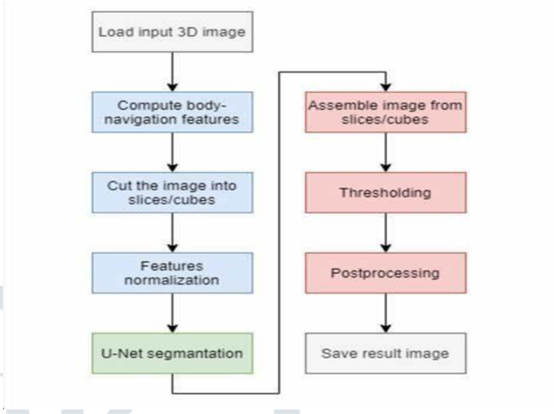

Figure:7 Output of the segmentation step.

3.5. Classification:

This completes the process of making predictions. This step's goal is to display the classifier's (T/S CNN) output. A member of one of the three classes—normal, benign, or malignant—is the classifier's output. Numerically speaking, the prediction procedure requires the use of a mathematical function. The soft max function is employed in this instance for multi-classification. Generally speaking, mapping the non-normalized output to a probability distribution over anticipated output classes is a common usage for neural networks[49].

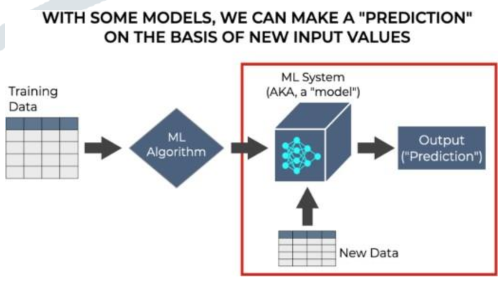

Figure:8 output classes of the prediction process.

4. Result:

200 mammogram pictures are used in the context of these examinations, with the results being determined without the influence of shift and scaling issues. CNNS techniques outperform TCNN and SCNN in terms of accuracy, sensitivity, precision, recall, times of performance, and quality of picture metrics when compared to equivalent approaches based on KNN and RF. It shows in fig.9.

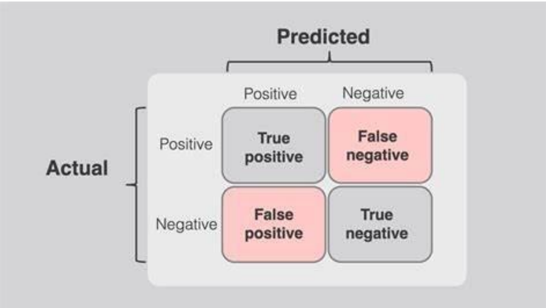

Figure:9 Result predicted.

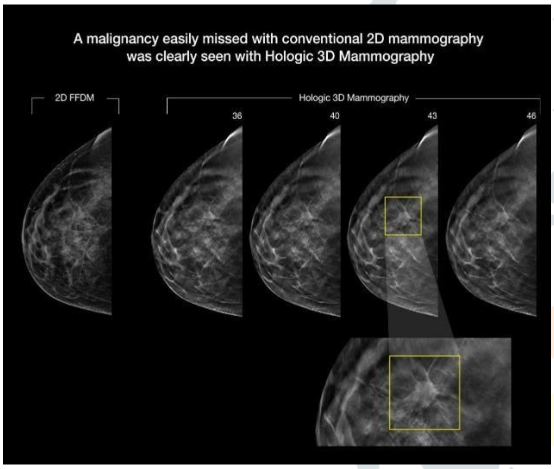

Figure:10 Mammogram images.

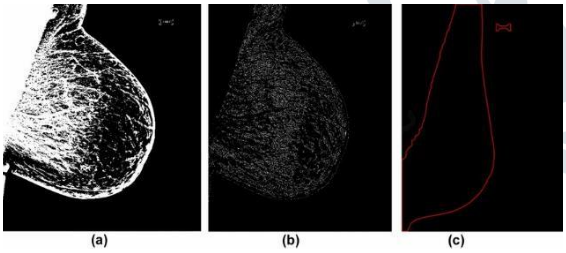

Figure:11 An example of the mammogram image a before; b after Canny algorithm for edge detection; and c with algorithm-detected edge of breast region.

5. Conclusion:

In the field of medicine, diagnosis is crucial to saving patients' lives. This is especially important in situations like breast cancer, where early diagnosis of the disease is crucial. The

accuracy of diagnosis becomes crucial when using machine learning to create diagnoses for doctors. This is due to the fact that errors in diagnosis might occasionally result in death. In the medical field, accuracy and processed image blurring are closely related. Using the

200 breast mammography images from the MIAS dataset, which is made available online, the suggested CNN and SCNN techniques are trained and evaluated. The suggested CNN and SCNN methods are assessed using various confused matrix-based matrices and contrasted with other methods of a similar nature. While the RF-based and KNN-based methods demonstrated accuracies of 78% and 74%, respectively, the SCNN and TCNN attained accuracies of 95% and 92%. The accuracy scores for both the TCNN and the SCNN indicate that they are promising techniques with potential applications in the medical field.

They also discuss the obstacles that must be removed in order for DL approaches to be successfully implemented in clinical settings

.

References

[1] Hicks, who C., and Wu, J. (2021). Machine learning for the classification of breast cancer types. 11(2), 61 in Journal of Personalized Medicine.

[2] M. Islam, M. Haque, M. Hasan, M. Hasan,
M. Iqbal, & M. N. Kabir (2020). A comparative study employing machine learning approaches for the prediction of breast cancer. 1–14 in SN Computer Science, 1(5).

[3] Olugbara, O. O., Mshelia, M. D., Adebiyi,
M. O., and Arowolo, M. O. (2022). A Breast Cancer Diagnosis Linear Discriminant Analysis and Classification Model. 11455; Applied Sciences, 12(22).

[4] Alazzam, M. B., Maabreh, R. S. A., and AlGhamdi, A. S. (2021). Machine learning techniques for predicting breast cancer patients'survival curves.Biomechanics and Applied Bionics, 2021.

[5] In 2021, Magboo, M. S. A., and Magboo,
V. P. C. Classifiers for Machine Learning in Breast Cancer Recurrences. Computer ScienceProcedia,192,2742–2752.

[6] Hu (2021), Sun (2021), Yuan (2021), andWu (2021). Deep residual learning for classifying the histological picture of breastcancer. 31(3), 1583–1594, International Journalof Imaging Systems and Technology.

[7] Saha, S., and N. Arya (2021). Advanced deep learning rchitectures using multiple modalities to predict breast cancer survival.Systems Based on Knowledge, 221, 106965.

[8] "Deep learning for image-based cancer detection and diagnosis− a survey," by Hu, Zilong, and colleagues. 134–149 in Pattern Recognition 83 (2018).

[9] A thorough evaluation of artificial neural network-based breast cancer screening was conducted by Bharati S., Podder P., and Mondal
M.R.H. 2020;12:125–137; Int. J. Comput. Inf. Syst. Ind. Manage. Appl. [Scholar Google]

[10] Alom, M.Z., Taha, T.M., Yakopcic, C., Nasrin, M.S., Hasan, M., Van Essen, B.C., Awwal, A.A.S., Asari, V.K., Westberg, S., Sidike, P. A Comprehensive Overview of Advanced Theory and Architectures for Deep Learning. Electronics 8:292 (2019). [CrossRef]doi:10.3390/electronics8030292.[Scholar Google