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DEVELOPMENT AND DIAGNOSIS OF BREAST CANCER USING MULTI-MODAL DATASETS

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Abstract:

This study suggests a Convolutional Neural Network based Computer Aided Diagnosis model for the detection and diagnosis of breast cancer. It is mainly done using the three datasets for accurate prediction and classification. Such as MIAS and DDSM dataset of the Mammography images and BUS dataset of the Ultrasound images. Five learnable layers make up the primary CNN model: one fully connected layer and four convolutional layers. With fewer parameters, the model makes it easier to automatically extract significant characteristics from breast cancer pictures, and it is a good fit for a variety of machine learning applications. The model includes several elements, such as transfer learning techniques and high-level feature learning. Extensive simulation results on breast cancer image datasets depicts that the model performs better in terms of performance metrics and training speed of the dataset. It also eliminates the need of the traditional handcraft feature selection and extraction steps. Data augmentation is the primary method used to lessen the model's overfitting and produce good results for each dataset. [2] The proposed Hybrid CNN based CAD model provides good accuracy in available three datasets and is evaluated using different performance metrics and methods. On top of that, we have used some predefined CNN Models like VGG-16, ResNet-50, Inception V3, MobileNet V2, DenseNet-169 to enhance our model's accuracy and provide faster training speed of the MIAS, DDSM and BUS datasets, respectively.

Keywords: CNN, CAD, VGG-16, ResNet-50, Inception V3, DenseNet-169, MobileNet V2

I. INTRODUCTION

The second most common cause of death among women is breast cancer, and early identification and diagnosis are crucial to reducing mortality. Once the cancerous cells begin to form in the breast, they swiftly move to other organs. According to the Globo-can project report, India has a death rate of about 87,090 per year and 162,468 new cases of breast cancer. Research teams studying medical image processing are always focused on creating novel screening tools and early cancer diagnosis. Because early and automated cancer diagnosis reduces costs and saves time. The most helpful methods for detecting and diagnosing breast cancer are mammograms and ultrasounds; good prediction requires a qualified radiology technician.[12] Thus, in order to interpret pictures from the Mammography and Ultrasound datasets for precise identification and diagnosis, a strong convolutional neural network (CNN) model and computer-aided diagnosis (CAD) model must be developed.

Machine learning techniques are crucial for the breast cancer categorization. CNN techniques are thought to be well-suited for many machine vision applications since they automatically extract the features. Layers of CNN model-There are just five learnable layers in the CNN model: one fully connected layer, four convolutional layers, and one. With fewer parameters, it assists in automatically extracting salient elements from the photos. For reliable results, this study suggests an effective CNN model with a straightforward design and minimal parameters.

Advantages of CAD model- Compared to other current CAD models, the CNN-based approach provides a number of benefits: i. Model eliminated traditional handcraft feature extraction and selection tasks. ii. In terms of training, it is quicker than other plans. iii. In the training phase, fewer parameters are needed. iv. The model avoids overfitting issues and offers improved accuracy.[11] Problem statement- Past Computer-Aided Diagnosis systems showed the potential for improving accuracy using different models and methods like SVM & CNN. But it has a lot of limitations like less accuracy, small datasets & random image selection. So, there was the need for such a model that can solve the above problems with high efficiency and accuracy.

II. LITERATURE REVIEW

The majority of automated CAD models created with various machine learning techniques produce good performance results in a range of applications. D. Muduli proposes a convolutional neural network (CNN) model for automated classification of breast cancer utilizing an alternate picture class: mammograms and ultrasounds. [1] Better classification performance was demonstrated by S. Beura's CAD model [5], which is based on the discrete wavelet transform (DWT) with GLCM features and a back-propagation neural network (BPNN) classifier. The KNN classifier and DWT and GLCM features of the CAD model have been suggested. Liu introduced a model that uses a support vector machine (SVM) classifier in conjunction with the principal component analysis (PCA) reduction approach on DWT features.[4] Support vector machines are used in the classification of breast masses in digital mammograms by Alhabib, M., and Basheer, N. (2013). Basheer suggested a CAD model that included SVM and DWT.[13] Convolutional neural networks are used for representation learning in the classification of mass lesions in mammography. Biomed. 127 (2016): 248–257. J. Arevalo, F.A. Gonzalez, R. Ramos-Pollan, & J.L. Oliveira, M.A.G. Lopez, Computer Methods Programs.[14] John proposes a hybrid CNN model with preprocessing and supervised learning as two of its phases. Using the raw pixels of the image as input, the model performs a sequence of non-linear transformations to learn a hierarchical representation of the visual information contained in the image.

A different CNN model is proposed, and it outperforms earlier preset CNN models such as VGG16, ResNet50, and InceptionV3, which are assessed on INbreast and trained on the DDSM dataset.[11] A CNN model built on a learning YOLO detector is proposed, and a shared dataset is used to evaluate a number of learning classifiers, including ResNet-50, and InceptionV3,Resnet-V2.Multi-scale CNN model that included global and local features using feature map creation using the multi-class and DensNet & MobileNet for feature extraction, as proposed by L. Xie.[2]A more comprehensive feature-based CNN model was put out by, which tested on the DDSM dataset and integrated the features of many predefined CNN models. A CNN model based on textural information derived from local binary patterns (LBPs) has since been suggested. Rahman has created InceptionV3 and ResNet50, two modified CNN models. Dhungel suggested a CNN model that is feature-based, meaning that a random forest (RF) classifier comes after CNN to extract features. Chougrad has experimented with many CNN models to decide the optimal fine-tuning technique and has suggested the significance of transfer learning. [15] It is evident that CNN's inherent benefits in feature extraction and reduction feature make it a popular choice for a variety of applications. Thus, a CNN-based method was developed for classifying breast cancer using mammography data.

III. METHODOLOGY

3.1 Dataset collection:

For Mammogram images, the MIAS and DDSM datasets are the two accessible datasets for mammography images. The three categories of normal, benign, and malignant photos are present in the databases, which total 326 and 1500 images, respectively. MIAS dataset images has pixel size of 1024* 1024 pixels and for DDSM dataset image the pixel size is of 598*598 pixels. For Ultrasound images, BUS dataset is available, which consists of 1578 images with the size of 500*500 pixels. It is categorized into three classes: malignant normal, benign images.[12] The BUS breast cancer dataset consists of 780 images. When paired with machine learning, breast ultrasound pictures can yield remarkable outcomes in the identification, classification, and segmentation of breast cancer. when coupled with machine learning, results in the categorization, detection, and segmentation of breast cancer.

3.2 CNN Model:

Machine learning techniques are crucial for the categorization of breast cancer. CNN-based techniques are thought to be well-suited for many machine vision applications since they automatically extract the features from the dataset images. It consists of 5 layers: 1) Convolution Layer: This fundamental building element allows the input picture to be utilized to create many feature maps, each of which controls a parameter, learns a neighboring pixel, and uniformly identifies an image. 2) Batch normalization Layer: Throughout the training process, it offers autonomous learning capabilities for every layer that is utilized to normalize the input over mean and standard deviation. 3) ReLU Layer: The CNN model's common activation layer, which guarantees non-linearity of output and promotes quicker convergence, computational efficiency, and the elimination of gradient issues. 4) Pooling Layer: By lowering the settings, it helps to down sample the feature maps and fixes over-fitting problems. 5) Fully connected Layer: This layer generates a single vector by merging all the learnt features from the earlier levels. To boost efficiency and lower the computational cost of training, this model also uses a small number of fully connected layers.

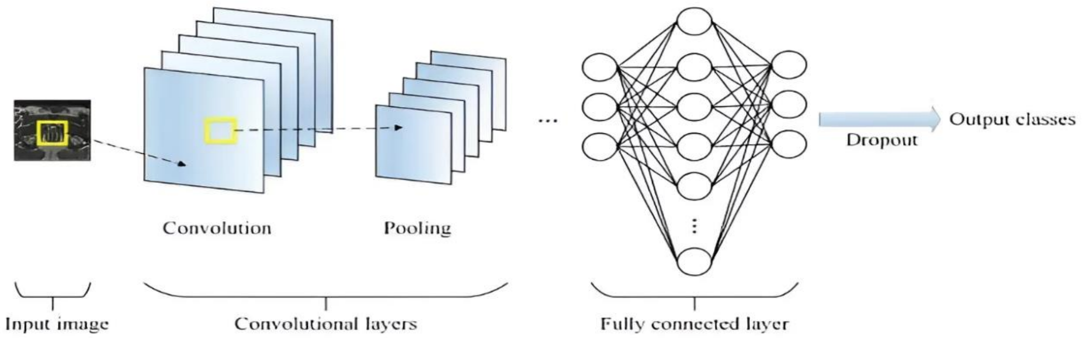

Figure 1: Typical CNN Model Framework

3.3 CAD Systems:

Automated methods for diagnosis or detection were created utilizing computers, AI, computer vision, and image processing to aid medical specialists in correctly identifying medical pictures by increasing image quality and clearly emphasizing salient regions. It also enables clinicians to swiftly assess and analyse the irregularity and make recommendations. The fundamental purpose of CAD systems is to discover uncommon symptoms that a medical expert would overlook and to give superior diagnostic assessments. Another reason why CAD is chosen for breast screening is due to its ability to detect defects before symptoms develop. as a second opinion to overcome experts' subjective evaluations. A typical CAD system workflow include the following steps:

a. Input Image: Digital mammography/ ultrasound images or other breast medical serve as input.

b. Preprocessing: Converting medical image into a suitable format and preprocessing techniques to enhance image quality and remove noise.

c. Segmentation: Identifying isolated breast region from background. Segment suspicious mass regions and microcalcifications using DL.

d. Feature Extraction: Extract shape, texture, and intensity features from segmented regions to differentiate tissue and find the abnormalities.
e. Classification: Utilize ML to classify regions as benign or malignant. Then evaluate performance metrics like accuracy, precision, and recall.

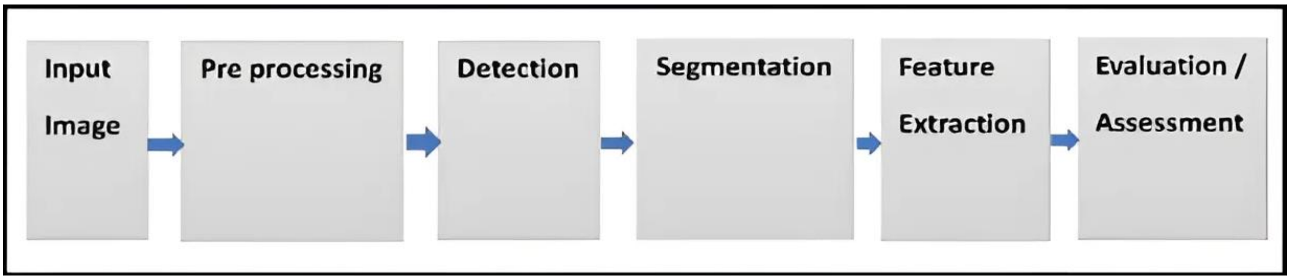

Figure 2: Workflow of CAD System in Breast Cancer Diagnosis

3.4 Proposed Model:

In fig.1, we have a proposed Hybrid CNN based CAD Model which mainly consists of 4 Stages for efficient and accurate classification of breast cancer. The 4 stages are as follows: 1. Image Preprocessing. 2. Image Data Augmentation. 3. CNN Model. 4. Implementing Classifiers or Predefined CNN Models.

Firstly, we have breast cancer images of Mammography and Ultrasound Dataset from the Kaggle website. In the 1st Stage, all the dataset images were pre-processed to enhance the breast cancer images which helps in reducing noise and we performed exploratory data analysis of the dataset. In the second stage, it creates a number of several photos during the training of the breast cancer dataset using Image Data Augmentation method, which improves the learnable features. In the 3rd Stage, we train and test our CNN Model using transfer learning and various functions like Accuracy & Loss function, CCE loss function, etc. In the 4th Stage, to improve our model performance we implemented some predefined CNN models like VGG-16, ResNet-50, Inception V3 to extract the best from the dataset images. Finally, we validate each dataset by finding the metrics like accuracy, precision, recall, F1 score and visualize it better with the help of graphs.[10]

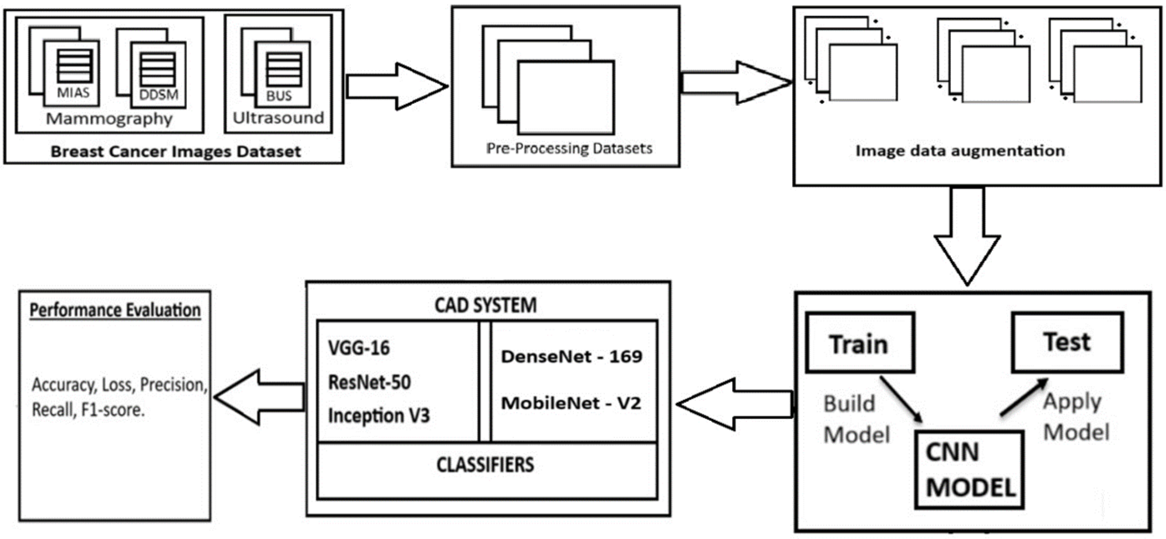

Figure 3: Hybrid CNN based CAD Block Diagram

3.5 Hybrid CNN Based CAD Model:

Here, it combines the power of CNN model with CAD system to enhance the accuracy and robustness of system during the breast cancer detection and diagnosis. Here's how it can be implemented: 1) Data Collection: Collect the available datasets of Mammogram and Ultrasound images, each labelled with information about the presence or absence of breast cancer. 2) Preprocessing: Preprocessing the images to enhance the quality of images, reduce noise, and standardize their size for consistency. 3) Model Architecture: Designing a CNN model for image classification. Typically, it includes multiple convolutional layers for feature extraction and a few pooling layers for dimensionality reduction and for an efficient model. [14] 4) Training: Training the CNN model on labelled dataset using techniques such as transfer learning, where you fine-tune it using the pre-trained CNN model (e.g., model trained on ResNet-50 & VGG-16 data). 5) Testing: Testing the trained CNN on new, unlabeled mammogram images to assess its ability to detect breast cancer.6) Validation: Evaluating the model's performance by finding the metrics like Accuracy, Precision, etc. [10]

3.6 Predefined CNN Models:

Pre-defined CNN (Convolutional Neural Network) models are pre-trained neural networks that have been trained on large datasets for various computer vision tasks. These models serve as feature extractors or classifiers for a wide range of image-related tasks and are available for use in deep learning frameworks like TensorFlow and PyTorch. Below are definitions for some popular pre-defined CNN models: 1) The concept of residual connections, which solve the vanishing gradient problem in very deep networks, was first introduced by the deep neural network architecture ResNet-50 (Residual Network with 50 layers). It consists of 50 layers and has demonstrated excellent performance in tasks like image classification and feature extraction. 2) The University of Oxford's Visual Geometry Group created the convolutional neural network model known as the VGG-16 (Visual Geometry Group 16-layer model). It is renowned for its strength and ease of use in picture classification jobs, and it has 16 weight layers. 3) A deep convolutional neural network model called Inception V3 is a member of the Inception architectural series, commonly referred to as Google Net. It is designed to achieve high computational efficiency and excellent accuracy by using multiple parallel convolutional operations. Commonly used for image recognition and classification. 4) DenseNet-169 is a CNN design distinguished by its dense connection among layers. It is made up of many dense blocks, each with numerous convolutional layers and pooling layers for down sampling feature maps. It offers an appropriate mix between model complexity and performance, making it ideal for medical image analysis applications. 5) MobileNet V2 has advantages in terms of computing efficiency and allows for accurate breast cancer diagnosis. It is chosen for its lightweight architecture, which efficiently balances model size and accuracy. The pictures undergo preprocessing techniques such as scaling and normalization to reduce noise and improve image quality.

IV. RESULTS AND DISCUSSIONS

The CNN-based CAD model is assessed using performance metrics on several datasets, including the BUS, DDSM, and MIAS datasets including pictures of breast cancer detected by ultrasound and mammography. Here, the performance metrics like Accuracy, F1 Score, Precision, Recall Value is calculated. Where CNN models show detailed layers information along with the number of parameters and output shape of the layers. The Predefined CNN model for Breast Cancer Detection provides better accuracy and faster training speed in breast cancer datasets.[7] So, in this project we have worked on both CNN and other predefined CNN models to achieve better accuracy and faster training speed with a smaller number of parameters.

4.1 Mammography Images

4.1.1 MIAS Dataset:

The study utilizes mammographic images from the MIAS dataset for breast cancer-related machine learning tasks. Fig.2 provides a visual overview of the dataset, while Fig.3 identifies and ranks the top 10 classes in breast cancer severity through machine learning predictions. [9] Additionally, Fig.3 visually represents the correlation between different features in the MIAS breast cancer dataset, revealing insights into data relationship. As seen in Fig. 4, the research goes on to apply a Convolutional Neural Network model for cancer detection. Furthermore, the study also evaluates the performance metrics of predefined CNN models applied to the MIAS dataset, offering detailed results in Table 1. These findings contribute to a quantitative understanding of performance in breast cancer detection using the MIAS dataset.[4]

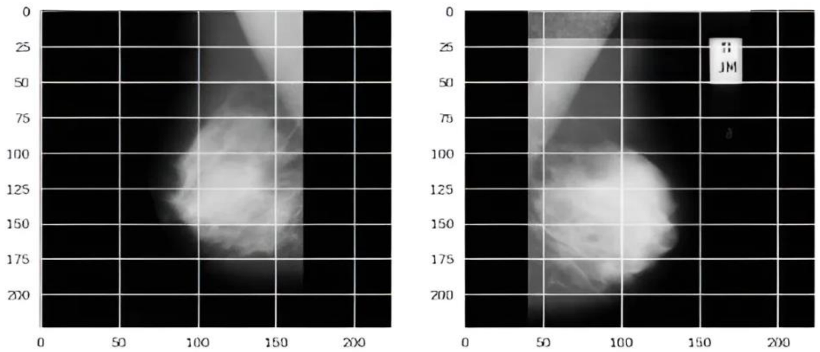

Figure 4: MIAS Dataset Breast Cancer Image

Table 1: Performance of Hybrid CNN based CAD Model Information

Models	Accuracy	F1 Score	Recall	Precision
Inception V3	83.7%	83.9%	83.69%	83.74%
VGG-16	93.8%	93.78%	93.78%	93.77%
ResNet-50	96.1%	96.1%	96.1%	95.9%
DenseNet169	85.4%	85.3%	85.4%	85.3%
MobileNetV2	85.8%	85.9%	85.8%	86.4%

4.1.2 DDSM Dataset:

The study employs various visual and analytical components for breast cancer analysis using the DDSM dataset. Fig.5 showcases a sample image from the DDSM dataset, emphasizing visual characteristics of mammographic data used in breast cancer research. Details on the CNN model architecture used with the DDSM dataset are shown in Fig. 5. Furthermore, Table 2 offers a summary of the performance metrics of predefined CNN models on the DDSM dataset, emphasizing key metrics for a comprehensive evaluation of model effectiveness in breast cancer analysis.[8]

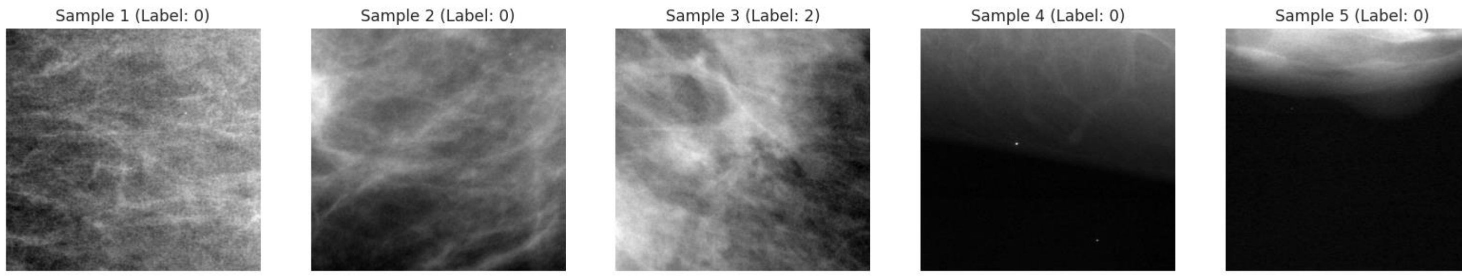

Figure 6: DDSM Dataset Sample Images

Table 2: Performance of Hybrid CNN based CAD Model on DDSM Dataset

Models	Accuracy	F1 Score	Recall	Precision
InceptionV3	79.2%	74.5%	64.6%	75.1%
VGG-16	73.4%	70%	68.1%	75.4%
ResNet-50	89%	73.8%	69.3%	76%
DenseNet169	80.5%	72.5%	71.2%	76.4%
MobileNetV2	86.9%	80.9%	86.9%	75.6%

4.2 Ultrasound Images

4.2.1. BUS Dataset:

Research shows a multifaceted analysis of breast cancer utilizing the Breast Ultrasound (BUS) dataset. Fig.6 differentiates and compares normal and masked ultrasound images, crucial for understanding features relevant to breast cancer detection using ultrasound data. Furthermore, Table 3 evaluates the performance metrics of predefined CNN models on the BUS dataset, providing valuable insights into their effectiveness for breast cancer analysis. Together, these components contribute to a comprehensive understanding of breast cancer detection using ultrasound data.[3]

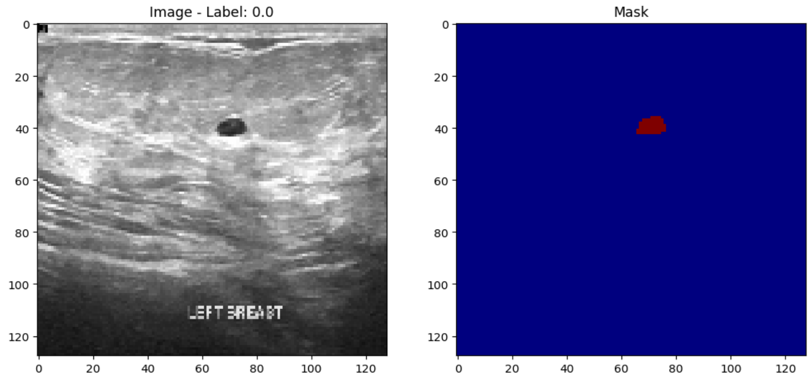

Figure 6: Ultrasound Normal and Masked Image

Table 3: Performance of Hybrid CNN based CAD model on BUS Dataset

Models	Accuracy	F1 Score	Recall	Precision
Inception V3	71.5%	76.2%	77.8%	78.1%
VGG-16	74.2%	70.7%	76.4%	74.3%
ResNet-50	79.7%	80.1%	79.6%	79.2%
DenseNet169	85.7%	85.8%	85.7%	85.6%
MobileNetV2	89.3%	89.4%	89.3%	89.3%

V. CONCLUSION

In this work, we have presented a Hybrid CNN-based CAD model that uses Mammogram and Ultrasound images to detect and diagnose breast cancer. The main CNN model consists of five learnable layers, comprising of four convolution layers and one fully connected layer. The model eliminates the need of manual handcraft feature extraction and reduction task, which results in quicker version of this model in terms of detection and diagnosis in the early stages. The model provides advantages such as good accuracy, faster training speed, requires less parameters. It also provides better knowledge of results with the help of performance metrics like Accuracy, Precision, Recall, F1 score and visualization using the line, bar graphs. Proposed Model aims to detect and diagnose breast cancer in its early stages, which would help in less time-consuming and cost-effective therapy as well as contribute in noble cause for the future medical research work.

VI. REFERENCES

[1] D.Muduli, R. Dash, B. Majhi, Automated diagnosis of breast cancer using multi-modal datasets: A deep convolution neural network-based approach, Biomedical Signal Processing and Control 71, Elsevier (2022) 1746-8094.

[2] L. Xie, L. Zhang, T. Hu, H. Huang, Z. Yi, Neural networks model based on an automated multi-scale method for mammogram classification, Knowl. -Based Syst. 208 (2020) 106465.

[3] U. Dafni, Z. Tsourti, I. Alatsathianos, Breast cancer statistics in the European union: incidence and survival across European countries, Breast Care 14 (6) (2019) 344–353.

[4] K. Liu, G. Kang, N. Zhang, B. Hou, Breast cancer classification based on fully connected layer first convolutional neural networks, IEEE Access 6 (2018) 23722–23732.

[5] S. Beura, B. Majhi, R. Dash, Mammogram classification using two-dimensional discrete wavelet transform and gray-level co-occurrence matrix for detection of breast cancer, Neurocomputing 154 (2015) 1–14.

[6] H. Mohamed, M.S. Mabrouk, A. Sharawy, Computer aided detection system for micro calcifications in digital mammograms, Comput. Methods Programs Biomed. 116 (3) (2014) 226–235.

[7] A. Jalalian, S.B. Mashohor, H.R. Mahmud, M.I.B. Saripan, A.R.B. Ramli, B. Karasfi, Computer-aided detection/diagnosis of breast cancer in mammography and ultrasound: a review, Clin. Imaging 37 (3) (2013) 420– 426.

[8] N.I. Yassin, S. Omran, E.M. El Houby, H. Allam, Machine learning techniques for breast cancer computer aided diagnosis using different image modalities: a systematic review, Comput. Methods Programs Biomed. 156 (2018) 25–45.

[9] D.R. Nayak, R. Dash, B. Majhi, R.B. Pachori, Y. Zhang, A deep stacked random vector functional link network autoencoder for diagnosis of brain abnormalities and breast cancer, Biomed. Signal Process. Control 58 (2020) 101860.

[10] G. Litjens, T. Kooi, B.E. Bejnordi, A.A.A. Setio, F. Ciompi, M. Ghafoorian, J.A. Van Der Laak, B. Van Ginneken, C.I. Sanchez, ´ A survey on deep learning in medical image analysis, Med. Image Anal. 42 (2017) 60–88.

[11] X. Jiang, Y.-D. Zhang, Chinese sign language fingerspelling via six-layer convolutional neural network with leaky rectified linear units for therapy and rehabilitation, J. Med. Imaging Health Inform. 9 (9) (2019) 2031–2090.

[12] S.-H. Wang, J. Sun, P. Phillips, G. Zhao, Y.-D. Zhang, Polarimetric synthetic aperture radar image segmentation by convolutional neural network using graphical processing units, J. Real-Time Image Process. 15 (3) (2018) 631–642.

[13] M. Alhabib, N. Basheer, Classification of Breast Cancer diagnosis Mammograms using support vector machines. (2013).

[14] J. Arevalo, F.A. Gonz´alez, R. Ramos-Poll´ an, J.L. Oliveira, M.A.G. Lopez, Representation learning for mammography mass lesion classification with convolutional neural networks, Comput. Methods Programs Biomed. 127 (2016) 248–257.

[15] A.S.A. Rahman, S.B. Belhaouari, A. Bouzerdoum, H. Baali, T. Alam, A.M. Eldaraa, Breast mass tumor classification using deep learning, in: 2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies (ICIoT), IEEE, 2020, pp. 271-276