

<sup>1</sup>Dr. T Sunil Kumar<sup>2</sup>Gujjeti Sridhar<sup>3</sup>Dr. D Manju<sup>4</sup>P Subhash<sup>5</sup>Gujjeti Nagaraju

# Breast Cancer Classification and Predicting Class Labels Using ResNet50



**Abstract:** - Numerous studies have been conducted using Deep Learning paradigms to detect Breast Cancer. Breast cancer is a medical condition where abnormal cells in the breast grow uncontrollably, forming tumors. If not treated, these tumors can metastasize and spread to other parts of the body, potentially leading to life-threatening consequences. In the year 2020, there were approximately 2.3 million cases of breast cancer diagnosed in women, leading to around 685,000 deaths worldwide. By the close of 2020, there existed 7.8 million women who had been diagnosed with breast cancer within the preceding five years, solidifying it as the most widespread form of cancer globally. Breast cancer is observed across all countries, affecting women at various ages post-puberty, with incidence rates tending to rise in older age groups. The aim of this paper is to classify and predict the class labels of breast cancer. To achieve this, a ResNet50 model is utilized and mammography images are employed to locate cancer within the image and classify it to emphasize the affected area. The ResNet50 identifies mass regions and classifies them as either ductal carcinoma, inflammatory, triple negative or invasive cancer. The experimentation is carried out on breast cancer dataset and achieved 90.6% accuracy both for classification as well as prediction

**Keywords:** Artificial Intelligence, Breast Cancer Classification, Deep Learning, Mammogram Images, ResNet50.

## I. INTRODUCTION

Breast cancer, characterized by uncontrolled cell proliferation in the breasts, is one of the leading causes of cancer-related deaths among women worldwide. Its diverse forms, each with unique characteristics, pose significant challenges in diagnosis and treatment. Early detection is crucial, as it increases the likelihood of successful treatment and reduces the need for invasive procedures. However, existing breast cancer detection technologies often result in false positives, leading to unnecessary and expensive medical interventions [1].

In the realm of breast cancer diagnosis, several critical issues have emerged that necessitate immediate attention. Foremost among these is the inadequacy of early detection methods. Many women are subjected to aggressive treatments with diminished survival prospects and enduring physical scars due to the late detection of breast cancer. Compounding this problem is the prevalence of false positives in current detection technologies, leading to unnecessary, invasive, and financially burdensome procedures. Furthermore, there is a significant gap in the detection and categorization of early-stage breast cancer, which, if undiagnosed, can proliferate and metastasize. Additionally, most existing studies and methodologies focus primarily on the presence of cancer, neglecting the crucial aspect of identifying specific types of breast cancer [2]. This oversight hinders the development of targeted treatment plans and underscores the need for more refined and nuanced diagnostic techniques. Therefore, there is a pressing need for advancements in breast cancer detection that not only enhance early diagnosis but also accurately classify the cancer type, paving the way for more effective and personalized treatment strategies.

This research addresses a critical need in the field of breast cancer diagnosis by focusing on the development of more accurate and early detection methods. The inadequacies of current detection techniques, marked by high rates of false positives and a lack of specificity in identifying cancer types, underscore the urgent requirement for improved methodologies. Our study introduces [3] an innovative application of the ResNet50 model, renowned for its efficacy in image classification, tailored specifically for the nuanced task of classifying different types of breast cancer in mammography images. The approach combines advanced image processing techniques, including noise reduction, segmentation, blob analysis, and Otsu's binary thresholding, with deep learning algorithms. This dual-module system not only enhances the precision of detecting breast cancer at its early stages but also categorizes

<sup>1</sup>Professor ,Dept. of CSE-(CyS,DS) and AI&DS , VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India  
Email id: sunilkumar\_t@vnrvjiet.in

<sup>2</sup>Assistant Professor ,Dept. of CSE , Kakatiya Institute of Technology & Science, Warangal, India, Email Id: gs.cse@kitsw.ac.in

<sup>3</sup>Corresponding author: Assistant Professor ,Dept. of CSE-(CyS,DS) and AI&DS , VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India, Email Id:nuthana525@gmail.com

<sup>4</sup>Associate Professor ,Dept. of CSE-(CyS,DS) and AI&DS , VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India , Email ID: subhash.parimalla@gmail.com

<sup>5</sup>Assistant Professor ,Department of CSE, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India.

Email id: Nagaraju.gujjeti@gmail.com

Copyright © JES 2023 on-line : journal.esrgroups.org

the cancer into specific types, namely Inflammatory, Invasive, Triple Negative, and Ductile Carcinoma. By bridging these gaps in current diagnostic practices, our research aims to significantly improve the accuracy of breast cancer detection and facilitate the development of more effective, personalized treatment plans, thus marking a pivotal advancement in the medical field [4].

The research utilizes the CBIS-DDSM[5]: Breast Cancer Image Dataset, comprising mammogram images that include various types of breast cancers. This dataset provides a comprehensive ground for training and evaluating the ResNet50 model. The dataset's diversity and complexity offer an opportunity to test the model's efficacy in identifying and classifying different breast cancer types.

The primary goal of this research is to enhance breast cancer detection and classification using the ResNet50 model. The motivation is driven by the need for more accurate, efficient, and less invasive breast cancer detection methods. By focusing on the classification of cancer types, this study aims to contribute to personalized and precise medical interventions.

### **Key Contributions of the Research**

1. Advanced Classification Techniques: Introducing a novel application of the ResNet50 model in classifying different types of breast cancer from mammogram images.
2. Enhanced Accuracy and Efficiency: Demonstrating improved accuracy in breast cancer detection and classification compared to traditional methods.

The paper is organized into several sections: a literature survey, detailing previous works and setting the context for this study; the architecture of the ResNet50 model used; detailed methodology including data preprocessing, model training, and implementation; results and discussion, where the outcomes of the study are analyzed; and finally, a conclusion summarizing the findings and implications of the research.

## II. LITERATURE SURVEY

The literature survey presents a comprehensive overview of the current landscape of breast cancer diagnosis, encompassing a range of machine learning and deep learning techniques. These studies collectively highlight the advancements and challenges in breast cancer diagnosis, emphasizing the potential of machine intelligence techniques and deep learning in improving diagnostic accuracy and patient outcomes.

- **Combination of Machine Learning Techniques in Breast Cancer Diagnosis:** A study explored the efficacy of an ensemble approach combining SVM, LR, NB, and DT in diagnosing breast cancer, highlighting its effectiveness in both upsampled and regular datasets. However, the emergence of more advanced models, particularly CNNs, poses a challenge to these traditional methods in automatic breast cancer detection [6].

- **Automatic Segmentation and Classification of Breast Masses:** Another research developed a technique for automatic segmentation and categorization of breast masses using sequential digital mammograms, offering a significant advancement in imaging analysis [7].

- **Training Data Enhancement for D-CNN:** The focus of this research was on generating effective training data for Deep Convolutional Neural Networks (D-CNN). A notable limitation was the potential alteration of images due to added noise, possibly diminishing the model's performance [8].

- **Deep Learning in Predicting Invasive Cancer:** This study compared deep learning models with traditional regression methods in predicting invasive breast cancer. It outlined three distinct CNN architectures, achieving an accuracy of 87%. The reliance on secondary databases like Kaggle was noted as a limitation, suggesting future research should employ primary data for more accurate breast cancer detection [9].

- **CNN Models in Breast Cancer Histopathology:** The paper highlighted the preference for CNN models over traditional learning methods due to their speed and reliability. The study reviewed binary, four, and eight classifications of breast cancer using the Break His database, noting the influence of image resolution on model performance. The high cost of high-resolution imaging equipment was acknowledged as a challenge [10].

- **Automated Detection of Breast Cancer in Histopathology Images:** This study aimed to develop a highly accurate method for early cancer detection using the best available dataset for breast histology images. However, it did not sufficiently investigate patient-level accuracy due to dataset limitations, particularly the lack of individual patient photo information [11].

- **AdaBoost Algorithm with Deep Learning Assistance:** The AdaBoost algorithm, enhanced with deep learning, was proposed for early breast cancer diagnosis and detection. The DLA-EABS method showed high accuracy and

outperformed existing methods, though the small dataset size limited its accuracy. The study suggested the potential of incorporating other deep learning models like Fast CNN and RCNN to improve accuracy [12].

- **Thermography in Breast Cancer Diagnosis and CNN Performance:** This paper discussed the role of thermography in diagnosing breast cancer and enhancing CNN performance through data augmentation. The study found that simpler CNN architectures often outperform more complex ones. A significant limitation was the scarcity of available data, especially high-quality breast thermal images [13].

- **Hybrid Deep Learning Model Evaluating Breast Cancer Risk:** A hybrid deep learning model combining full-field mammograms and conventional risk factors was found to be more accurate than the Tyrer-Cuzick model. The study used data from a single vendor and academic institution, and the reliance on breast tissue density as a risk factor was a noted limitation [14].

- **Deep Feature Fusion in Breast CAD:** The research introduced a breast Computer-Aided Diagnosis (CAD) technique based on deep feature fusion targeting mass detection and diagnosis. It showed superior performance over existing methods in a study of 400 female mammography cases. The study highlighted the effectiveness of combining deep features with ELM for breast cancer diagnosis [15].

The literature survey identifies several research gaps in breast cancer diagnosis, including limited utilization of advanced models like CNNs, challenges in image quality and noise management, reliance on secondary data sources, lack of comprehensive patient-level analysis, and data scarcity and equipment limitations. To address these gaps, the proposed work aims to extensively use advanced CNN models, enhance image quality and noise reduction techniques, incorporate primary data sources, conduct detailed patient-level analysis, overcome data and equipment challenges, and explore advanced deep feature fusion techniques. These approaches aim to improve the accuracy and applicability of breast cancer diagnosis, ultimately leading to better patient outcomes.

### III. PROPOSED ARCHITECTURE

The proposed architecture involves the development of a breast classification model based on ResNet50, which is designed to analyze mammogram images for the automated identification of regions of interest related to mass abnormalities. These abnormalities are then categorized as inflammatory, ductile carcinoma, invasive, or triplenegative cancer. The model utilizes preprocessing and augmentation techniques to establish initial weights for training, employing the CBIS-DDSM: Breast Cancer Image Dataset. Image augmentation is applied to generate additional images, enhancing diversity and reducing overfitting. The proposed method is visually represented in a figure 1. This approach aligns with the broader research landscape, which emphasizes the application of convolutional neural networks (CNNs) for breast cancer detection and classification, showcasing the potential of deep learning in addressing critical healthcare challenges.

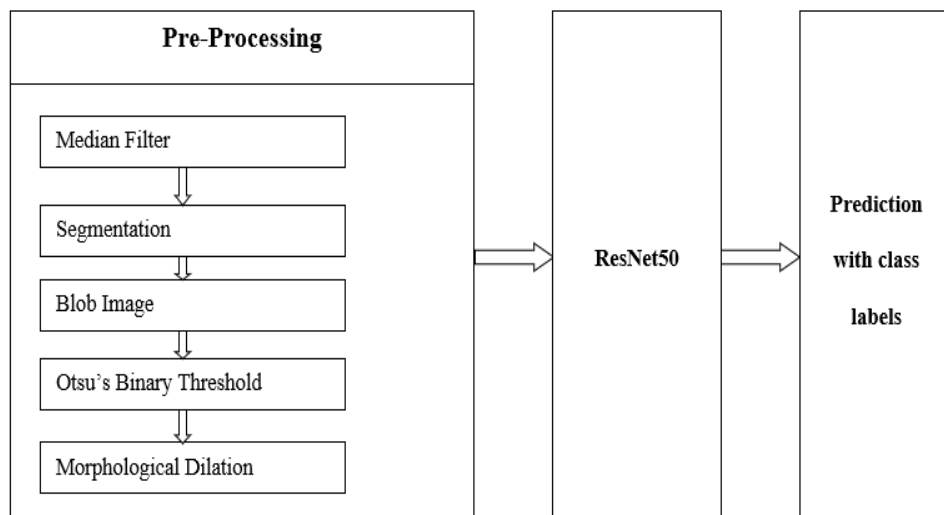


Fig.1, The block diagram of ResNet50 for prediction task.

The steps of the current work are as follows:

#### A. Data Acquisition

The dataset employed in this study is the CBIS-DDSM (Curated Breast Imaging Subset of DDSM), which consists of mammography (MG) images from breast cancer patients.

### B. *Image Preprocessing for Mammographys*

The goal of preprocessing was to enhance the quality of the data for effective deep learning training. The following steps were undertaken:

#### **Noise Reduction with Median Filtering:**

Algorithm Description:

Input: A grayscale image  $I$  of dimensions width  $w$  and height  $h$ , with a specified window size  $n \times n$ .

Step 1: Initialize an output image  $R$  with dimensions identical to  $I$ .

Step 2: Pad image  $I$  to handle edge pixels. The padding depends on the oddity of  $n$ :

- For odd  $n$ , pad  $\frac{n-1}{2}$  pixels on each side.
- For even  $n$ , pad  $\left(\frac{n}{2}\right) - 1$  pixels on one side and  $n/2$  on the other.

Step 3: Process each pixel  $(x, y)$  in  $I$ :

- Extract a  $n \times n$  window centered at  $(x, y)$  from the padded image.
- Sort the pixel values in this window.
- Set the pixel  $(x, y)$  in  $R$  to the median value from the sorted window.

Output: The filtered image  $R$ .

Operational Principle: The median filter, by replacing each pixel with the median value in its surrounding window, effectively removes 'salt-and-pepper' noise while preserving essential image features like edges. This median-based approach is less prone to the influence of outliers compared to mean-based filtering[17].

Enhancing the Mammogram: The breast region was isolated from non-essential elements such as background, artifacts, labels, and patient information in the MG images. This was achieved using Otsu's thresholding technique, which significantly improved the clarity and focus of the images for subsequent analysis.

### C. *Watershed Algorithm for Image Segmentations*

Computing Watershed Lines ( $L$ ):

- Initialization: Create a label matrix  $L$ , same size as image  $I$ , initializing all pixel values to 0.
- Marker-Based Flooding: Flood-fill the image with each marker's index until boundaries are reached, marking visited pixels in  $L$ .
- Topological Sorting: Sort the markers based on their flood-fill completion times.
- Marker Merging: In the sorted order, merge markers in  $L$  with their nearest neighbours if they share the same grayscale value  $G$ . Continue merging until all markers are processed or no further merges are possible.

Outputting the Final Segmentation ( $S$ ):

- Labeling Regions: Label each region, defined by watershed lines in  $L$ , as a separate object in the segmented **image**  $S$ .
- Assigning Pixel Labels: Each pixel in  $S$  is labeled according to the marker responsible for its watershed line.

### D. *Blob Detection Technique*

#### **Applying Laplacian of Gaussian (LoG) Filter:**

### E. *Otsu's binary thresholding*

Otsu's binary thresholding [19] is an automated method widely utilized in image processing and computer vision for optimal image segmentation. It distinguishes between foreground and background by analyzing the grayscale image's histogram to find the threshold that minimizes class variance. This technique is pivotal in applications like object detection, character recognition, and medical image analysis.

Algorithm for Otsu's Binary Thresholding:

- Input Preparation:  
Take a grayscale image  $I$  with dimensions width  $w$  and height  $h$ .
- Histogram Computation:

Calculate histogram  $H$  for  $I$ , covering intensity levels from 0 to 255.

Normalize  $H$  so its values sum up to 1.

Variable Initialization:

- Total pixels  $n = w * h$ .
- Initialize background weight  $wB = 0$ , foreground weight  $wF = 0$ .
- Initialize sums  $sumB = 0$  (background intensities),  $sumF = 0$  (foreground intensities).
- Initialize between-class variance  $varBetween = 0$  and optimal threshold  $threshold = 0$ .

Threshold Calculation:

- For each potential threshold  $t$  (0 to 255):
- Update weights and sums:
 
$$wB += H(t), wF = n - wB, sumB += t * H(t), sumF -= t * H(t).$$
- Calculate between-class variance:  $varBetween = wB * wF * \left( \left( \frac{sumB}{wB} \right) - \left( \frac{sumF}{wF} \right) \right)^2$ .
- Update threshold if  $varBetween$  exceeds current maximum.

Binary Image Formation:

- For each pixel  $(x, y)$  in  $I$ :
  - If  $I(x, y) > threshold$ , set  $binaryImage(x, y) = 1$  (foreground).
  - Otherwise, set  $binaryImage(x, y) = 0$  (background).

Output:

The segmented binary image, where pixels are classified as foreground or background based on the Otsu-determined threshold.

This process results in a binary image where each pixel is categorized as either foreground or background, depending on its value relative to the optimal threshold established by Otsu's method.

#### F. Morphological algorithm

This operation is crucial in binary image processing, aiming to expand object boundaries. It involves a structuring element sliding over the image, turning a pixel in the output image to 1 whenever any part of this element overlaps with a foreground pixel in the input image. The dilation's extent is governed by the structuring element's size and shape, which can be tailored for specific effects like filling gaps or enlarging objects for easier detection.

#### Algorithm:

- Input: A binary image (width , height ) and a structuring element ( )
- Initialization: Create an output image with the same dimensions as setting all pixels to 0.
- Processing:
  - For each pixel in I
  - Overlay the center of on S on P
  - If S overlaps with a foreground pixel in set the corresponding pixel in to I
- Output: The processed image O

#### G. Model Training with ResNet-50

- ResNet-50, a variant of Residual Networks, is a profound solution to the vanishing/exploding gradient problem in deep convolutional neural networks. It is designed with 50 layers, including convolutional, pooling, fully connected layers, and crucially, shortcut connections.
- Concept of Residual Learning: The key innovation is the use of shortcut connections (also known as skip connections or identity mappings) to facilitate residual learning. This technique allows the network to focus on learning the difference between the input and desired output, rather than relearning complete mappings
- Architecture and Functionality:
  - Layers: The model comprises 50 layers, forming the architecture of ResNet-50.
  - Residual Blocks: It features residual blocks with multiple convolutional layers and shortcut connections.

- Purpose: The additional layers in ResNet-50 are intended to learn increasingly complex features. For instance, while initial layers may learn basic features like edges, subsequent layers progressively detect more complex attributes such as textures and objects.
- Solution to Gradient Issues: The increasing depth often leads to vanishing/exploding gradients in traditional networks. ResNet-50 addresses this through skip connections, directly transmitting information to subsequent layers, thus preventing gradient diminishment.
- Identity Functions Learning: Skip connections also enable the model to learn identity functions.
- Ensuring that higher layers are at least as effective as lower ones, if not better.

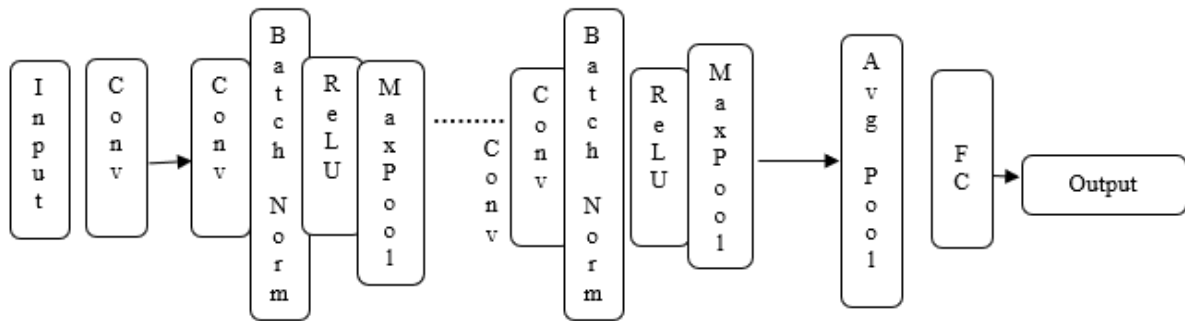


Fig.2, ResNet50 Architecture.

Enhanced Performance with ResNet-50 in Deep Neural Networks: ResNet-50, a deep neural network model, has markedly improved performance in computer vision, especially in tasks like image classification, object detection, and image segmentation. Its proficiency is evident through its state-of-the-art results on major datasets like ImageNet, which contains millions of categorized images. This has led to its widespread adoption in both computer vision and medical imaging fields. The entire model employs stochastic gradient descent (SGD) optimizers, with TensorFlow as the backend, and is developed using Python and Keras[16].

Adapted Approach with ResNet-50: The approach adapts the original ResNet-50 model by incorporating additional features. It includes an attention mechanism utilizing a local max pooling layer for dimension conversion. Instead of merely detecting cancer presence, the algorithm classifies cancer types. The process starts with convolutional layers in the neural network processing the input, followed by the attention technique transforming the 2D image into a 1D format for feature mapping. Subsequently, the model conducts classification and regression to localize the cancer in mammography images and identify its type.

Dataset Structure for Cancer Classification: The dataset is divided into training and testing sets, further subdivided into four categories representing different cancer types: Invasive, Inflammatory, Triple Negative, and Ductile Carcinoma. Each category contains 70 mammography images. The division into test and training data, with these detailed subdivisions, facilitates a comprehensive analysis for the classification of cancer types.

#### IV. RESULTS AND DISCUSSION

Dataset and Interface Utilization: For our experimental analysis, the CBIS-DDSM (Curated Breast Imaging Subset of DDSM) Breast Cancer Image Dataset was utilized. Additionally, a graphical user interface (GUI) was developed to effectively display the outcomes of the experiment.

Process and Output: The primary input for this system is a mammogram image. The process begins with the application of preprocessing techniques to this image. Key steps in this process include the application of blob detection and Otsu's binary thresholding methods.

The outcome of these techniques is twofold:

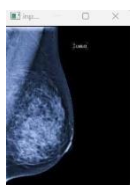

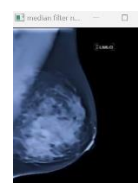
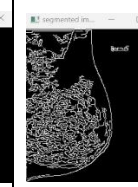
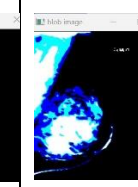
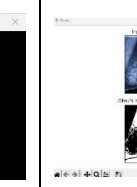
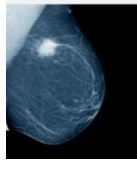
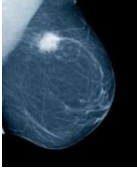
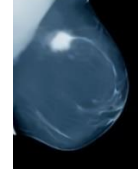
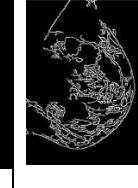
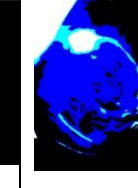

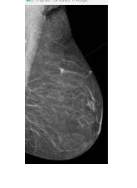
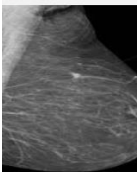
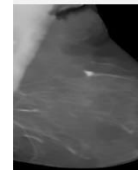
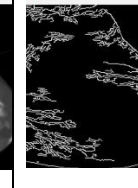
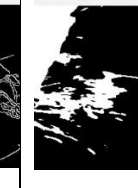

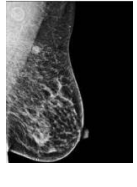
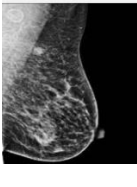
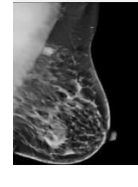
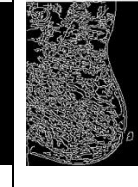


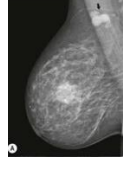
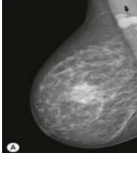
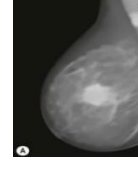
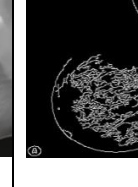
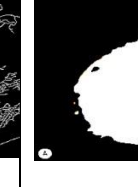
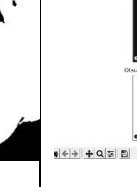
1. Area Calculation: The processed image enables precise calculation and display of the area affected by potential cancerous growths.
2. Localized Image Display: The GUI showcases the localized areas of interest within the mammogram, highlighting regions where abnormalities were detected.

Steps Yielding the Output: The following sequence of operations leads to the final output:

- Preprocessing: The mammogram image undergoes initial preprocessing to enhance its quality for further analysis.
- Blob Detection and Thresholding: Employing blob detection and thresholding methods provides a detailed perspective of the image, focusing on areas of concern.
- Area and Localization Analysis: The resultant data include both the quantified area of potential abnormalities and their precise localization within the mammogram.
- Display via GUI: Finally, the processed data is visualized on the GUI, providing a clear and user-friendly representation of the findings.

This approach effectively combines advanced image processing techniques with user-centric display methods, resulting in a comprehensive and accessible system for breast cancer image analysis.

Table 1. Output generated for different test cases.

S.N o.	Input Image	Output of Fundus Image	Median Filter Output	Segmentation	Blob Image	Otsu Method	Effected Area Output
1.							Loaded model from disk C:/Users/WAJIHA KULSU inflammatory_cancer area 43.190144
2.							C:/Users/WAJIHA KULSU inflammatory_cancer area 45.537495
3.							C:/Users/WAJIHA K invasive_cancer area 69.11255
4.							ductal_carcinoma area 51.69867 Loaded model from disk
5.							C:/Users/WAJIHA KUI triple_negative_canc area 82.7333

The research output presented in Table 1 illustrates a systematic process for analyzing mammogram images to detect and quantify potential breast cancer lesions. Each row in the table corresponds to a distinct test case, providing a step-by-step visualization of the analytical methods applied and their outcomes.

Here is a detailed analysis:

1. **Input Mammogram Images:** The process begins with raw mammogram images, which serve as the starting point for detection and analysis.

2. **Median Filter Application:** The images are subjected to a median filtering process, which likely serves to reduce noise and improve clarity. This step is crucial for ensuring that subsequent analysis is based on accurate and artifact-free data.

3. **Segmentation Results:** Following noise reduction, segmentation techniques are applied. These techniques are designed to separate potential areas of concern (likely indicative of cancerous tissue) from the normal background tissue within the mammogram.

4. **Blob Detection:** The images are then processed through blob detection algorithms. This stage is aimed at identifying and highlighting discrete objects within the image, which, in this context, would be the suspected cancerous lesions.

5. **Selected Analytical Method:** This column, though not fully legible, seems to indicate the application of a specific method chosen for further processing the detected regions. The exact nature of this method is not clear from the image provided.

6. **Quantified Area of Concern:** The final column reveals the localized images of the detected areas, complete with quantified data. This data likely represents the size or scale of the lesions, which is essential for assessing the stage and potential severity of the cancer.

Overall, the table 1 captures the multi-stage process of identifying, isolating, and measuring areas of potential breast cancer in mammogram images using advanced image processing techniques. The sequential approach—from raw image through preprocessing, segmentation, and quantification—highlights the meticulous methodology employed to arrive at the final analyzed data, which is critical for accurate diagnosis and treatment planning. Each step in the table is instrumental in refining the analysis, ensuring that the final output is both precise and informative for medical professionals.

## V. CONCLUSION

This study is dedicated to the classification and precise localization of cancerous regions within mammography images. It distinguishes between different cancer types—ductal carcinoma, triple-negative, inflammatory, or invasive—and accentuates the affected areas for better visualization and analysis. The methodology starts with median filtering to reduce image noise, followed by segmentation to identify regions of interest. The blob detection technique is then applied to analyze the morphological features, and Otsu's binary thresholding delineates these features by differentiating pixels based on intensity levels. ResNet50, chosen for its accuracy and capability to handle image inputs directly, facilitates the pixel-level prediction and classification. Leveraging its sophisticated architecture and pretrained capabilities, ResNet50 is adept at handling medical imaging tasks, such as the detection and localization of breast cancer. The culmination of these techniques, with the assistance of ResNet50, aims to advance the early detection and accurate diagnosis of breast cancer, achieving a notable accuracy rate of 90.6% in identifying and categorizing mass regions into specific cancer types.

## REFERENCES

- [1] Corsetti, V., Houssami, N., Ferrari, A., Ghirardi, M., Bellarosa, S., Angelini, O., ... & Ciatto, S. (2008). Breast screening with ultrasound in women with mammography-negative dense breasts: evidence on incremental cancer detection and false positives, and associated cost. *European journal of cancer*, 44(4), 539-544
- [2] Redig, A. J., & McAllister, S. S. (2013). Breast cancer as a systemic disease: a view of metastasis. *Journal of internal medicine*, 274(2), 113-126.
- [3] Sushma Jaiswal, Harikumar Pallthadka, Rajesh P. Chinchewadi, & Tarun Jaiswal. (2024). A Deep Learning Model for Automatic Image Captioning using GRU and Attention Mechanism. *International Journal of Computer Engineering in Research Trends*, 11(1), 28–36.
- [4] Bianchi, P. H., Pereira, R. M., Zanatta, A., Alegretti, J. R., Motta, E. L., & Serafini, P. C. (2009). Extensive excision of deep infiltrative endometriosis before in vitro fertilization significantly improves pregnancy rates. *Journal of Minimally Invasive Gynecology*, 16(2), 174-180
- [5] Falconi, L. G., Perez, M., Aguilar, W. G., & Conci, A. (2020). Transfer learning and fine tuning in breast mammogram abnormalities classification on CBIS-DDSM database. *Adv. Sci. Technol. Eng. Syst. J*, 5(2), 154-165



- [6] Sushma Jaiswal, Harikumar Pallthadka, Rajesh P. Chinchewadi, & Tarun Jaiswal. (2023). Capturing the Essence: An In-Depth Exploration of Automatic Image Captioning Techniques and Advancements. *International Journal of Computer Engineering in Research Trends*, 10(12), 22–30.
- [7] Sushma Jaiswal, Harikumar Pallthadka, Rajesh P. Chinchewadi, & Tarun Jaiswal. (2023). Exploring a Spectrum of Deep Learning Models for Automated Image Captioning: A Comprehensive Survey . *International Journal of Computer Engineering in Research Trends*, 10(12), 1–11.
- [8] Abhijith Reddy Beeravolu, Sami Azam, Mirjam Jonkman, (Member, Ieee), Bharanidharan Shanmugam , (Member, Ieee), Krishnan Kannoorpatti, And Adnan Anwar, (Member, Ieee) “Preprocessing of Breast Cancer Images to Create Datasets for Deep-CNN ” *Digital Object Identifier*,0.1109/ACCESS.2021.3058773 March 3, 2021.
- [9] Poonam Jaglan, Rajeshwar Dass, & Manoj Duhan. (2019). Detection of Breast Cancer using MRI: A Pictorial Essay of the Image Processing Techniques. *International Journal of Computer Engineering in Research Trends*, 6(1), 238–245.
- [10] Faezehsadat Shahidi , Salwani Mohd Daud , (Member, Ieee), Hafiza Abas, Noor Azurati Ahmad, and Nurazeen Maarop “Breast Cancer Classification Using Deep Learning Approaches and Histopathology Image: A Comparison Study” *IEEE, Digital Object Identifier* 10.1109/ACCESS.2020.3029881, October 26, 2020.
- [11] YASIN YARI, THUY V. NGUYEN, AND HIEU T. NGUYEN “Deep Learning applied for historical Diagnosis of Breast Cancer” *IEEE, Digital Object Identifier* 10.1109/ACCESS.2020.3021557, September 17,2020.
- [12] Jing Zheng, Denan Lin, Zhongjun Gao, Shuang Wang, Mingjie He, And Jipeng Fan “Deep Learning Assisted Efficient AdaBoost Algorithm for Breast Cancer Detection and Early Diagnosis”, *IEEE Access*, June 4, 2020.
- [13] J. Zuluaga-Gomez, Z. Al Masry, K. Benaggoune, S. Meraghni, N. Zerhouni “A CNN based methodology for breast cancer diagnosis using thermal images”, *IEEE*,30 October 2019.
- [14] Pallavi P. Jadhav, & Prof. U. A. Nuli. (2017). Cancer Detection in Mammograms by Extracting Geometry and Texture Features. *International Journal of Computer Engineering in Research Trends*, 4(12), 552–555.
- [15] Zhiqiong Wang, Mo Li, Huaxia Wang, Hanyu Jiang, Yudong Yao , Hao Zhang, And Junchang Xin “Breast Cancer Detection using Extreme learning Machine-Based on Feature Fusion with CNN Deep Features”, *IEEE Access*, August 14, 2019

© 2023. This work is published under  
<https://creativecommons.org/licenses/by/4.0/legalcode>(the“License”). Notwithstanding the ProQuest Terms and Conditions, you may use this content in accordance with the terms of the License.