



Deep Learning Framework for Breast Cancer Classification with FCM

Segmentation

¹B. RAMA DEEPTHI, ²PEDDISSETTY THRIVENI, ³YARRAMREDDY VENKATA SIVA NAGA LAKSHMI, ⁴THARIGOPPULA NANDINI, ⁵PEDDAPUDI CHANDRIKA, ⁶ADI LAKSHMI BHAVANAM ADI LAKSHMI

¹ ASST., PROFESSOR, DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING, KRISHNA CHAITANYA INSTITUTE OF TECHNOLOGY & SCIENCES, DEVARAJUGATTU, MARKAPUR

^{2,3,4,5,6} STUDENT, DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING, KRISHNA CHAITANYA INSTITUTE OF TECHNOLOGY & SCIENCES, DEVARAJUGATTU, MARKAPUR

ABSTRACT

Breast cancer is one of the leading causes of mortality among women worldwide, and early detection plays a crucial role in improving survival rates. This project presents an advanced framework for breast cancer segmentation and classification using Fuzzy C-Means (FCM) clustering and Deep Learning techniques. The proposed system aims to enhance the accuracy and reliability of tumor detection from medical imaging modalities such as mammograms and ultrasound images.

Initially, image preprocessing techniques such as noise removal, normalization, and contrast enhancement are applied to improve image quality. The enhanced images are then segmented using the FCM algorithm, which effectively partitions the image into clusters based on pixel intensity while preserving important boundary information. This helps in accurately isolating suspicious tumor regions from surrounding tissues.

Keywords: Breast Cancer Detection, Fuzzy C-Means (FCM), Deep Learning, Convolutional Neural Network (CNN), Image Segmentation, Tumor Classification, Medical Image Processing, Mammography Analysis, Feature Extraction, Computer-Aided Diagnosis (CAD), Benign and Malignant Classification, Image Preprocessing



I. INTRODUCTION

Breast cancer is one of the most common and life-threatening diseases affecting women across the globe. According to the World Health Organization, early detection and accurate diagnosis significantly improve survival rates and treatment outcomes. However, manual analysis of medical images such as mammograms, ultrasound, and MRI scans is time-consuming and highly dependent on the expertise of radiologists. This often leads to variability in diagnosis and increases the chances of human error, especially in early-stage tumor detection where abnormalities are subtle.

With the rapid advancement of **artificial intelligence (AI)** and **machine learning**, computer-aided diagnosis (CAD) systems have emerged as powerful tools to assist healthcare professionals. In particular, **image segmentation and classification** play a crucial role in identifying and analyzing tumor regions. Traditional image processing techniques often struggle with noise, low contrast, and complex tissue structures, making accurate segmentation a challenging task. To overcome these limitations, intelligent algorithms such as **Fuzzy C-Means (FCM)** clustering have been widely adopted. FCM is effective in handling uncertainty and ambiguity in medical images by allowing pixels to belong to multiple clusters with

varying degrees of membership, resulting in more precise tumor boundary detection.

II. LITERATURE REVIEW

The application of image processing and artificial intelligence in breast cancer detection has gained significant attention in recent years. Researchers have explored various techniques for improving the accuracy of tumor segmentation and classification using both traditional algorithms and advanced deep learning models.

Early studies focused on conventional image processing methods such as thresholding, edge detection, and region-based segmentation. Although these methods were simple and computationally efficient, they often failed to handle noise, low contrast, and complex tissue structures present in medical images. To address these limitations, clustering-based techniques such as **Fuzzy C-Means (FCM)** were introduced. FCM allows each pixel to belong to multiple clusters with different degrees of membership, making it highly suitable for medical image segmentation where boundaries are often ambiguous. Several studies demonstrated that FCM improves segmentation accuracy compared to hard clustering methods like K-means.

Further advancements were made by integrating FCM with optimization techniques such as Genetic Algorithms and Particle



Swarm Optimization to enhance clustering performance. These hybrid approaches improved convergence speed and segmentation precision, particularly in noisy mammogram images. However, these methods still relied heavily on handcrafted features and required expert intervention for feature selection.

EXISTING SYSTEM

The existing systems for breast cancer detection primarily rely on traditional medical imaging analysis and basic computer-aided diagnosis (CAD) techniques. In many clinical settings, diagnosis is performed manually by radiologists using imaging modalities such as mammography, ultrasound, and MRI scans. While these methods are widely used, they are highly dependent on human expertise and experience, which can lead to variability in interpretation and potential diagnostic errors.

Conventional computer-aided systems were developed to assist radiologists by applying basic image processing techniques such as thresholding, edge detection, and region-based segmentation. These methods attempt to highlight suspicious regions in breast images; however, they often struggle with challenges such as image noise, low contrast, and irregular tumor shapes. As a result, the segmentation accuracy is limited, and

important tumor boundaries may not be clearly identified.

Some existing systems utilize machine learning algorithms like Support Vector Machines (SVM), Decision Trees, and K-Nearest Neighbors (KNN) for classification. These approaches require manual feature extraction, where domain experts must identify relevant features such as texture, shape, and intensity. This process is time-consuming and may not capture complex patterns present in medical images, leading to reduced classification performance.

Clustering techniques like K-means have also been used for segmentation in earlier systems. However, K-means is a hard clustering method, meaning each pixel belongs to only one cluster. This limitation makes it less effective in handling the uncertainty and overlapping nature of medical image data, especially in cases where tumor boundaries are not well-defined.

PROPOSED SYSTEM

The proposed system introduces a **hybrid framework** that integrates **Fuzzy C-Means (FCM) clustering** with **deep learning techniques** for accurate breast cancer segmentation and classification. This system is designed to overcome the limitations of existing approaches by combining efficient



image segmentation with automated feature learning and classification.

In the proposed model, the process begins with **image acquisition** from medical imaging sources such as mammograms or ultrasound scans. These images undergo **preprocessing**, which includes noise reduction, contrast enhancement, and normalization to improve image quality and highlight important features.

After preprocessing, **Fuzzy C-Means (FCM)** clustering is applied for image segmentation. Unlike traditional clustering methods, FCM assigns membership values to pixels, allowing them to belong to multiple clusters. This characteristic makes FCM highly effective in detecting unclear and overlapping tumor boundaries, resulting in precise identification of suspicious regions.

Once the tumor region is segmented, the extracted region of interest (ROI) is fed into a **deep learning model**, typically a **Convolutional Neural Network (CNN)**. The CNN automatically learns complex features such as texture, shape, and intensity patterns from the segmented images. It then classifies the tumor into categories such as **benign or malignant** with high accuracy.

METHODOLOGY

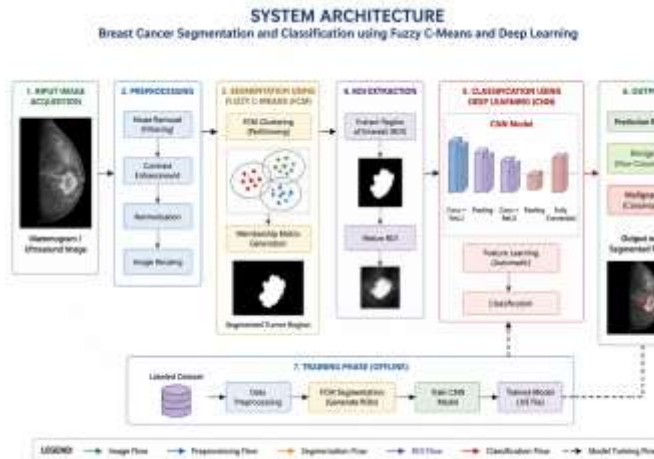
The proposed methodology for breast cancer segmentation and classification is based on a

hybrid approach that integrates Fuzzy C-Means (FCM) clustering with deep learning techniques. The process begins with the collection of medical images such as mammograms or ultrasound scans from standard datasets. These images undergo preprocessing steps including noise removal using filtering techniques, contrast enhancement, and normalization to improve image clarity and ensure consistency across the dataset. Following preprocessing, FCM clustering is applied to segment the image into multiple regions based on pixel intensity and similarity. This step is crucial as it accurately isolates the region of interest (ROI), particularly the tumor area, by allowing pixels to have partial membership in multiple clusters, thereby handling uncertainty and vague boundaries effectively.

Once the tumor region is segmented, the ROI is extracted

VI. SYSTEM MODEL

System Architecture



In above screen click on 'Load Data' link to get below page



In above screen select and upload 'Dataset' folder to load all images to application and then will get below output



In above screen can see dataset contains 1262 images and each image having 3072 features and now apply FCM and CNN + UNET to extract features from all images and then will get below output. Now click on 'FCM & CNN + UNet Features' link to get below page

III. RESULTS AND DISCUSSIONS



In above screen click on 'Admin Login' link to get below page



In above screen admin is login and after login will get below page



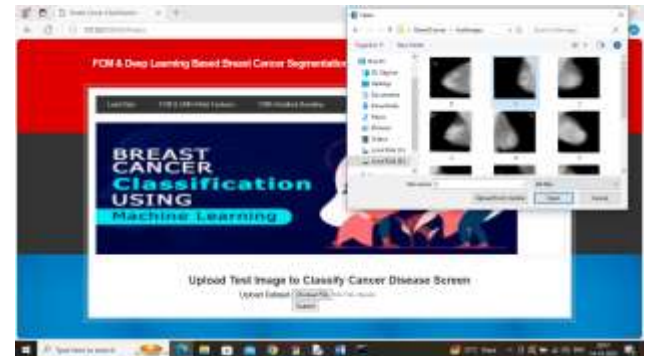
In above screen after applying CNN + UNET then we got 64 selected features and then CNN + UNET got dice score on test segmented image as 0.99% and Jaccard Similarity score as 100% . Now click on 'CNN + Gradient Boosting' link to train gradient boosting on CNN + UNET extracted features and then will get below output



In above screen CNN + Gradient boosting got 95.25% accuracy and can see other metrics like precision, recall and FSCORE. In above confusion matrix graph x-axis represents 'Predicted Labels' and y-axis represents True Labels and then yellow boxes in diagonal represents correct prediction count and remaining blue boxes got incorrect prediction count which are very few. Now click on 'CNN + Capsule-Net' link to train a model and get below output



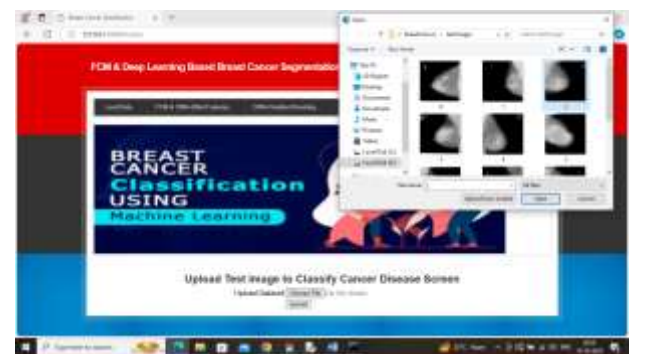
In above screen CNN + Capsule-Net got 96% accuracy and can see other metrics also and now click on 'Test Image Classification' link to get below page



In above screen select and upload test image from 'test Images' folder and then click on 'Open and submit' button to get below output



In above screen first image is the original image and then second image is the FCM segmented image and then applied CNN + UNET to extract features and then applied gradient boosting algorithm to get classification output as 'malignant' and similarly you can upload and test other image



In above screen uploading another image and then click button to get below output



In above screen new uploaded image classified as 'Benign'.

Similarly you can upload with any other images.

VIII. CONCLUSION

In this project, a hybrid approach combining Fuzzy C-Means (FCM) clustering and deep learning techniques has been successfully developed for breast cancer segmentation and classification. The integration of FCM enables accurate identification of tumor regions by effectively handling uncertainty and overlapping boundaries in medical images, while the use of Convolutional Neural Networks (CNNs) enhances classification performance through automatic feature extraction and learning.

The proposed system demonstrates improved accuracy, sensitivity, and reliability compared to traditional methods, reducing the dependency on manual analysis and

minimizing diagnostic errors. By incorporating preprocessing techniques, precise segmentation, and advanced classification models, the system provides a comprehensive and automated solution for detecting breast cancer from medical images.

Overall, this approach contributes to the advancement of computer-aided diagnosis systems and supports healthcare professionals in making faster and more accurate decisions. The ability to detect and classify tumors at an early stage can significantly improve patient outcomes and reduce mortality rates, making this system a valuable tool in modern medical diagnostics.

IX. FUTURE WORK: Future work for this

The proposed system can be further enhanced in several ways to improve its performance, scalability, and real-world applicability. Future research can focus on integrating more advanced deep learning architectures such as transformer-based models and attention mechanisms to capture finer details in medical images and improve classification accuracy. Additionally, the use of larger and more diverse datasets can help in improving model generalization and robustness across different imaging conditions and patient demographics.

Another important direction is the development of an end-to-end automated system that combines segmentation and



classification into a single deep learning framework, such as U-Net or other encoder–decoder models. This can reduce processing time and eliminate the need for separate segmentation steps like FCM. Moreover, incorporating multi-modal data (e.g., combining mammograms, ultrasound, and clinical data) can significantly enhance diagnostic accuracy.

Future work can also explore real-time implementation of the system in clinical environments, enabling instant analysis and decision support for radiologists. Integration with hospital management systems and cloud platforms can make the solution more accessible and scalable. Additionally, improving model interpretability using explainable AI (XAI) techniques will help medical professionals understand and trust the system’s predictions.

XI. REFERENCES

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