iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: IV Month of publication: April 2025

DOI: https://doi.org/10.22214/ijraset.2025.69320

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

Deep Learning Based Breast Cancer Detection Using Prababilistic Neural Network

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Abstract: Breast cancer is a major health concern affecting millions of women worldwide. Early detection greatly enhances survival rates and reduces the burden of treatment. This research presents a Computer-Aided Diagnosis (CAD) system that uses advanced image processing and deep learning techniques to classify mammographic images into benign or malignant categories. The system incorporates preprocessing, segmentation using Gaussian Mixture Models (GMM), feature extraction with Gray Level Co-occurrence Matrix (GLCM), and classification using a Probabilistic Neural Network (PNN). Developed in MATLAB and tested on the mini-MIAS database, the system achieved an accuracy of 99.4%, sensitivity of 99.3%, and specificity of 100%. This paper emphasizes the potential of automated systems in supporting medical diagnosis and enabling early intervention.
Keywords: Breast Cancer, Mammography, CAD, PNN, GLCM, GMM, Image Processing, Deep Learning, MATLAB

I. INTRODUCTION

Breast cancer is one of the leading causes of cancer-related mortality among women globally. According to the World Health Organization (WHO), breast cancer affects approximately 2.3 million women each year.Early detection is the key to effective treatment, especially in low-resource settings. Traditional diagnostic methods, such as biopsies and manual screening, are prone to delays and subjectivity. With the advancement of computational technologies, automated image-based diagnosis provides a more accurate and faster alternative. This research aims to implement a robust diagnostic tool using PNN and GLCM for texture-based classification.

II. LITERATURE REVIEW

Numerous methods have been proposed for automated breast cancer detection. Kourou et al. (2015) explored machine learning algorithms like Decision Trees and SVMs. Convolutional Neural Networks (CNNs) have also been widely used (Spanhol et al., 2016), especially in feature extraction and classification. However, PNN offers faster training, high accuracy. GLCM has shown effectiveness in capturing texture-based features, especially in mammographic images. Previous studies combining GLCM and PNN have demonstrated improved performance compared to conventional approaches (Sreedevi et al., 2020).

III. METHODOLOGY

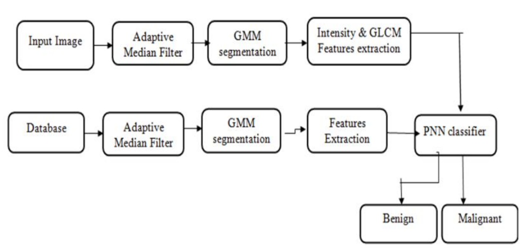

Figure 1: Block Diagram

A. Dataset

We used the mini-MIAS database, a standard benchmark for mammogram-based breast cancer research, containing 322 images labeled as normal, benign, or malignant. These images were collected from the United Kingdom's Mammographic Image Analysis Society and are widely accepted for CAD research.

B. Image Preprocessing

The input images are converted to grayscale and resized to 1024×1024 pixels to maintain uniformity. Noise is removed using Adaptive Median Filtering. Contrast is enhanced using Histogram Modified CLAHE and morphological dilation to emphasize microcalcification clusters. Histogram equalization adjusts intensity distributions to bring out tumor features clearly.

C. Segmentation

GMM-based segmentation separates regions of interest based on pixel intensity. Otsu's thresholding is applied to isolate microcalcifications from the background. Top-hat morphological operations help in removing uneven illumination and highlighting small bright lesions. The GMM clusters similar pixel values into probable tumor zones.

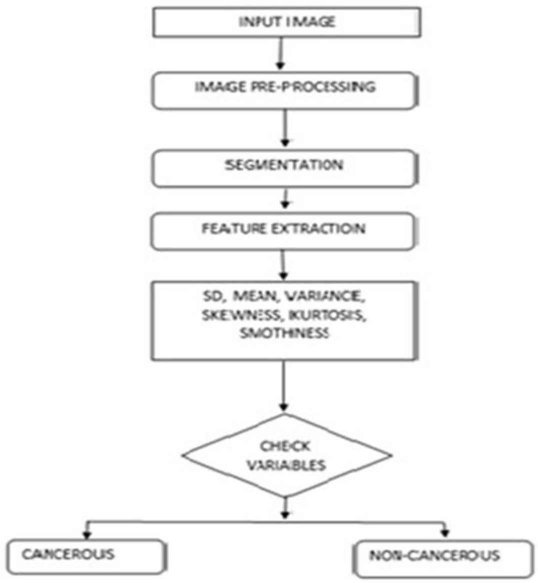

Figure 2: GMM segmentation

D. Feature Extraction

Texture features are extracted using GLCM along multiple orientations (0°, 45°, 90°, and 135°). Extracted features include contrast, energy, entropy, homogeneity, and correlation. These features are crucial in differentiating between tissue densities. Higher contrast values typically indicate abnormal cellular structures, which can signify malignancy.

E. Classification

PNN is employed for classification. The selected features are input to the PNN model, which outputs class labels (benign, malignant, or normal). PNN is chosen due to its low training time and probabilistic decision-making capability. It calculates a class probability function using the Parzen window estimator and Gaussian kernel, providing a reliable decision boundary even in overlapping feature regions.

IV. SYSTEM IMPLEMENTATION

A. Software Tools

1) MATLAB 2018a
2) GUIDE for GUI development

B. Hardware Requirements

1) Processor: Intel Core i5 (Dual Core)
2) RAM: 4 GB DDR III
3) Hard Disk: 500 GB
4) Monitor: 15" LCD
5) OS: Windows 10

C. Augmentation & Training

The dataset is expanded using data augmentation techniques such as rotation, mirroring, and flipping to address class imbalance. 70% of the images are used for training and 30% for testing. Training time was approximately 5 minutes using 100 epochs.

D. User Interface

A GUI is developed to allow image upload, real-time classification, and result visualization. It displays classification type and highlights cancerous regions.

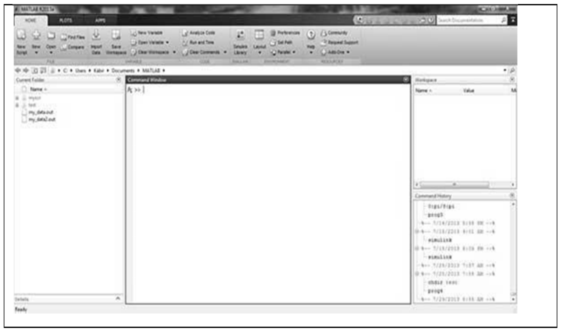

Figure 3: GUI

V. RESULTS AND EVALUATION

1) Accuracy: 99.4%
2) Sensitivity: 99.3%
3) Specificity: 100%
4) Precision: 98.9%
5) F1 Score: 99.1%
6) Processing Time per Image: ~1.2 seconds

These results confirm the efficiency of combining GLCM and PNN. The system handles noisy inputs and varying image quality efficiently. Augmentation significantly improved model generalization.

A. Performance Comparison

Method	Accuracy	Sensitivity	Specificity
SVM + GLCM	92.1%	89.5%	93.4%
CNN	95.7%	94.1%	96.2%
Proposed (PNN+GLCM)	99.4%	99.3%	100%

Limitations:

- The system is trained on a small dataset; performance on larger, real-world clinical datasets may vary.
- Only texture-based features were used; shape and edge-based features could further enhance accuracy.
- The MATLAB-based interface limits real-time deployment on mobile devices or embedded systems.

VI. CONCLUSION AND FUTURE SCOPE

This research successfully demonstrates the design and implementation of a CAD system using PNN and GLCM, capable of classifying breast cancer mammograms with high accuracy. The combination of adaptive preprocessing, texture-based feature extraction, and PNN classification leads to reliable diagnostic outcomes.

A. Future Work

- Integration with CNN architectures to combine spatial and texture features.
- Real-time deployment using embedded devices like Raspberry Pi for use in remote clinics.

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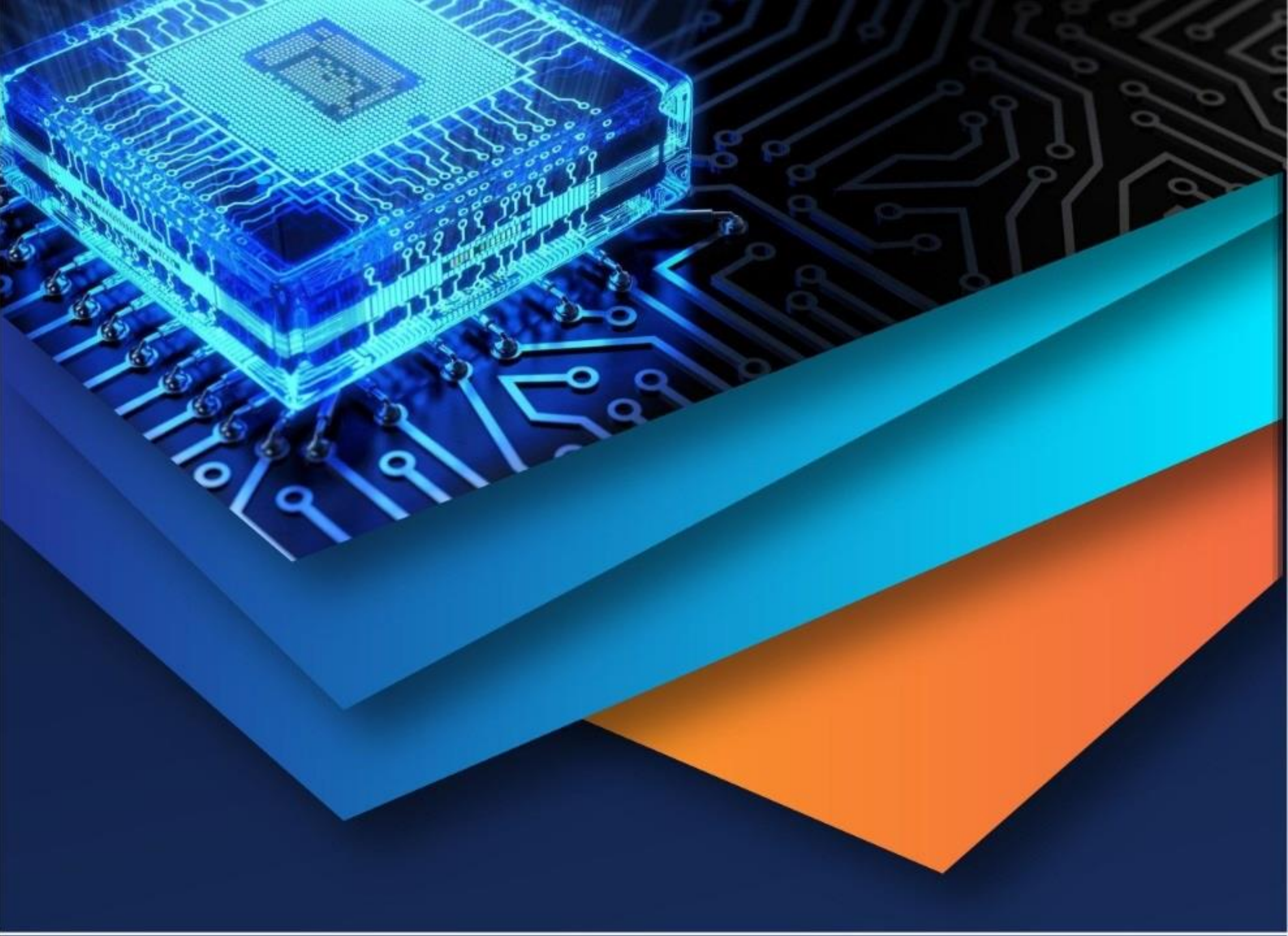

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