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Federated Learning Approach for Breast Cancer Detection

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Abstract

The most prevalent non-skin cancer in women and the second-leading cause of cancer death in women is Breast Cancer. Mammograms often show dense areas like breast tumours and lumps. A Malignant tumour typically has a jagged, rough, and hazy border; in contrast, a typical benign lump has a round, smooth, and well-defined border. By highlighting areas with a high suspicion of malignancy, Computer-aided detection (CAD) systems in screening Mammography act as a second opinion for radiologists. The ultimate objective of CAD is to reliably and accurately designate such places. Numerous studies have been conducted in order to predict cancer; various data mining techniques and algorithms were used by various researchers. Each approach has various drawbacks, such as a lack of intelligent prediction and inefficient structure, which inspired us to tackle this issue and put the Data Mining, based Cancer Prediction System into practise. So, a brand-new multi-layered approach that combines clustering and classification algorithms to create a system for predicting cancer risk is provided here. This method predicts breast cancers and is also user-friendly, time- and money-saving. The goal of this study is to detect prospective cancer patients using data mining techniques including classification, clustering, and prediction. The Support Vector Machine (SVM) technique is used to pre-process, feed into the database, and classify the collected data to produce meaningful patterns. We have suggested a data-driven cancer prediction method. This approach calculates the likelihood of developing breast cancer. This system's accuracy is verified by contrasting its anticipated outcomes with the patient's past medical history, and it was classified for analysis.

Keywords: Federated Learning, Breast Cancer Detection, Deep Convolutional Neural Networks (DCNN), Medical Imaging, Privacy-Preserving AI, Monarch Butterfly Optimization (MBO) SVM algorithm.

1 Introduction

Breast cancer remains a leading cause of cancer-related deaths among women. Early detection using AI-based medical imaging techniques has shown great promise. However, centralized deep learning models face challenges due to data privacy concerns, regulatory constraints, and data heterogeneity across institutions. Federated Learning (FL) addresses these issues by allowing models to be trained across multiple devices or hospitals without transferring raw data.Deep Convolutional Neural Networks (DCNNs) have proven effective in feature extraction and classification in medical imaging. However, selecting optimal hyperparameters remains a challenge. The Monarch Butterfly Optimization (MBO) algorithm is used to fine-tune DCNN parameters, improving performance. This study integrates FL, DCNN, and MBO to enhance breast cancer detection accuracy while maintaining patient data confidentiality.

2 Experimental Methodology

2.1 Dermoscopic Imaging and Skin Cancer

Dermoscopic plays a crucial role in skin and breast cancer detection by capturing high-resolution images of tissue abnormalities. The dataset includes mammographic and histopathological images from various medical sources, ensuring diversity and generalizability. **Dataset Details:** Sources, types of images, pre-processing.
textbfImage Acquisition Techniques: High-resolution imaging, augmentation.
textbfEthical Considerations: Patient confidentiality, dataset permissions.

2.2 DCNN Operations

Deep Convolutional Neural Networks (DCNN) are used for feature extraction and classification. The architecture consists of convolutional layers, pooling layers, batch normalization, and fully connected layers to analyze medical images. Feature extraction detects patterns in mammograms. ReLU , Sigmoid, and Softmax activation functions introduce non-linearity, while categorical cross-entropy is used as the loss function for multi-class classification.

2.3 Classifiers Based on Convolutional Neural Networks

Pre-trained Models: VGG16, ResNet50, Efficient Net.
Custom CNN Architectures: Modified models for breast cancer detection.
Comparison of Performance Metrics: Sensitivity, Specificity, AUC-ROC.

2.4 Monarch butterfly optimation (MBO)

MBO is a metaheuristic algorithm inspired by monarch butterfly migration patterns. It optimizes DCNN hyperparameters by: Tuning the learning rate, filter sizes, and batch sizes helps improve model convergence and accuracy while also reducing computational overhead, which is especially important in federated learning settings.

3 Preprocessing

Pre-processing steps ensure high-quality input data for training. The study includes diagrams featuring mammogram and histopathological image samples, along with a comparison of original and pre-processed images to highlight improvements. Dataset structures are presented in table format for clarity, while key formulas and normalization techniques are applied to ensure consistent and accurate model training.

4 Segmentation

4.1 Thresholding

Thresholding techniques separate cancerous and non-cancerous regions: Otsu's Thresholding is used for automatic threshold selection by maximizing variance between classes, while Adaptive Thresholding adjusts thresholds locally, making it effective for images with varying lighting conditions.

4.2 Morphological Operations

Morphological techniques improve segmentation accuracy when Erosion and Dilation are applied to refine lesion contours by shrinking and expanding image regions, while Opening and Closing operations help remove noise and smooth the boundaries for better image analysis.

5 Feature Extraction

Feature extraction enhances classification accuracy through texture features like GLCM and LBP capture patterns in the image surface, shape features such as circularity and aspect ratio describe the geometry of lesions, and intensity-based features through histogram analysis assess pixel value distributions for deeper image characterization.
Deep learning-based feature extraction techniques such as Convolutional Neural Networks (CNNs) are used to automatically learn important features from mammography images, while transfer learning leverages pre-trained models like VGG16 and ResNet50 to enhance feature extraction efficiency. Autoencoders further contribute by learning compact representations of breast tissue features. In the context of federated learning, local feature extraction is performed on client devices, such as hospitals, ensuring data remains private. These locally extracted features are then combined through global feature aggregation to train a robust global model. Secure multi-party computation techniques are employed to ensure the privacy and security of feature extraction and aggregation across different clients.

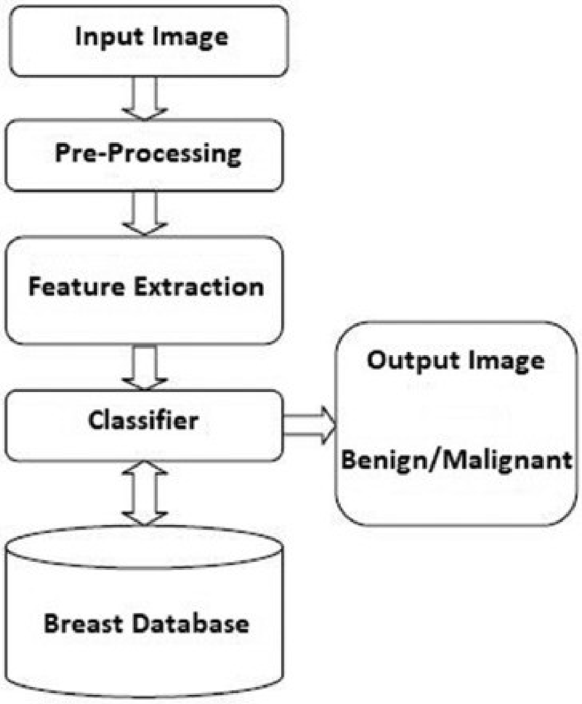

Figure 1: Flowchart

6 Result and Analysis

The performance of the FL-DCNN model is compared with centralized approaches using evaluation metrics: Federated Learning outperforms centralized models by maintaining data privacy and meeting privacy regulations through decentralized training, which prevents data leakage. Additionally, the use of MBO (Model-Based Optimization) improves hyperparameter tuning, leading to enhanced classification accuracy.

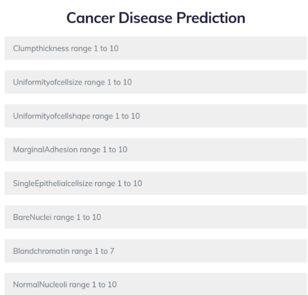

Figure 2:

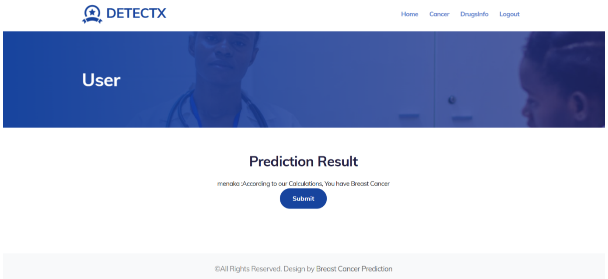

Figure 3:

7 Conclusion

This paper presents a Federated Learning-based breast cancer detection system utilizing Deep Convolutional Neural Networks and Monarch Butterfly Optimization. The results demonstrate that FL-DCNN achieves high classification accuracy while preserving data privacy. Future work includes enhancing security in FL training and incorporating additional imaging modalities.

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