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Deep Convolutional Neural Network–Based Image Processing for Automated Mammography Analysis and Breast Cancer Detection

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Abstract: The Deep Convolutional Neural Networks (DCNNs) model has become a prevalent model in image processing and computer vision tasks, and more specifically in the analysis and processing of biomedical images, because it can learn hierarchies of discriminative features by itself. Among many biomedical image modalities, the prevalent technique that has gained more attention and popularity in the early detection and diagnosis of breast cancer in its early stages of development is the mammography technique. Unfortunately, the analysis of these images in order for them to be utilized effectively by radiologists or experts in the field can be obstructed by many factors, such as the lack of contrast in images or the tissue patterns. A complete and integrated DCNN model for mammography image processing and early diagnosis of breast cancer, which comes out of an exhaustive doctorate program, is proposed and implemented in this study. Public and freely accessible datasets of images in the field of mammography, including MIAS, DDSM, and INbreast datasets, are utilized in order to verify and investigate the functionality of several models and learning approaches. The quality of images in datasets can be improved through Contrast Limited Adaptive Histogram Equalization (CLAHE) techniques, which are combined with new models in image feature learning like VGG-16, VGG-19, and ResNet-50 in the DCNN model. The main experimental outcomes reveal that ensemble models and learning techniques are more efficient and accurate in having increased accuracy and high AUC-ROC values, and sensitivity and specificity than those models and techniques utilized individually. In addition, these results show that it can be feasible to install and use the proposed model in Raspberry Pi 3B hardware and through a web application based on MobileNetV2.

Keywords: Deep Convolutional Neural Networks; Mammography; Breast Cancer Detection; Ensemble Learning; Transfer Learning; Medical Image Processing; Embedded Deployment

1. Introduction

Breast cancer is still recognized as one of the most frequent and deadly cancers worldwide and has contributed substantially to cancer morbidity and mortality. In fact, it is assumed that mammography is still the gold standard method currently used worldwide for population screening for breast cancer due to its cost-effectiveness and ability to visualize pathological changes such as microcalcifications and tumors at an early stage. However, mammography image analysis still faces some obstacles: low contrast and dense breast tissue images with overlapping anatomical information and artifacts. These obstacles may sometimes lead to false positives and missed diagnoses, thus confirming the need for CAD solutions. In conventional mammographic image processing, the image processing algorithms for mammograms have used hand-crafted features in combination with conventional image analysis methods such as filtering, thresholding, edge detection algorithms, and statistical feature extraction [4]–[6]. Even though conventional image analysis algorithms were useful in the development of first-generation CAD systems for mammograms, their performance is highly sensitive to expert-crafted features. As such, conventional image processing algorithms cannot generalize well with images taken with different image acquisition systems [7]. This has led to an interest in the use of advanced machine-learning techniques.

During the last few years, the area of image processing and computer vision underwent a paradigm shift via the emergence of Deep Learning, specifically the usage of Deep Convolutional Neural Networks (DCNNs) [8], [9]. DCNNs are engineered particularly to process the aforementioned grid-structured data, such as images, with the goal of extracting features automatically from raw pixel information without any need for manual preprocessing [9]. In contrast to typical ML approaches, DCNNs eliminate the need for manually engineered features using an end-to-end approach that combines both feature learning and classification [10]. This has been particularly true in the field of medical imaging, where DCNNs have made significant strides in radiology, pathology, and biomedical image analysis applications. DCNN-based systems have been highly sensitive and specific in identifying anomalies in a variety of imaging modalities, including MRI, CT, ultrasound, and mammography imaging [11]-[13]. In particular, for the purpose of detecting breast cancer, DCNNs have been successfully employed in the areas of mammography imaging classification, mass localization, microcalcification delineation, and risk assessment, accomplishing these objectives as well as, or sometimes even better, than expert radiologists [14]-[16]. Pre-trained models, like VGGNet, ResNet, and Inception models, based on the strength of these networks' ability to perform well in learning general-purpose features and then transfer learning in medical imaging applications, have been employed extensively [17].

Notwithstanding the above encouraging findings, a number of issues still persist regarding the application of DCNN-based systems for mammography. These issues include restricted access to large-scale databases with adequate annotations, class imbalance, high complexity, and hardware implementation issues in resource-constrained settings [18]. In this regard, a number of techniques have been proposed for overcoming the mentioned issues. These include transfer learning, ensemble learning, data augmentation, and the use of light CNN architecture designs [19-21]. As a result of these considerations, this research work proposes a holistic DCNN based framework for mammography image processing and breast cancer identification and characterization. The proposed framework examines different DCNN configurations and learning methodologies, such as transfer learning, scratch learning, and ensemble learning, on publicly available mammography image datasets like MIAS, DDSM, and INbreast. In addition, CLAHE based image preprocessing approaches can be used for improving contrast in mammography images with reduced contrast content. Moreover, this research endeavors to take a step further towards practical implementation of proposed DCNN based approaches and methodologies on a less computationally rigorous embedded system platform like Raspberry Pi 3B and a simple web application with MobileNetV2, thereby filling a possible gap between DCNN based research and its application towards early detection of breast cancer, among clinicians and medical professionals, respectively.

2. Related Work

Extensive research studies were carried out regarding the processing of mammography images and the diagnosis of breast cancer using conventional image processing methods as well as deep learning-based methods. The initial studies mostly concentrated on the design of feature extraction methods along with conventional machine learning classifiers. Spatial filtering, histogram-based thresholding, wavelet transform, edge detection, and morphology were used extensively for improving the quality of mammography images as well as identifying areas of interest [22]-[27]. Though these approaches had a reasonable level of success, these methods were highly dependent on expertly designed features. The increase in the capabilities of machine learning algorithms resulted in the combination of the features with the classifiers like Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Decision Trees (DT), and Random Forests (RF) in various researches. There was an advancement in the classification accuracies; yet, the researches faced challenges in terms of the possibilities of generalization, robustness to noise, and identification of the minute anomalies in the dense breast tissues [28] – [31]. The introduction of Deep Convolutional Neural Networks (DCNNs) represented a considerable shift in paradigm for the analysis of mammographic images. The possibility of deep networks in improving mammographic image analyses was illustrated by Sahiner et al. [45], emphasizing the significance of image quality in the training of deep models for superior performance. This was quickly followed by Kim et al. [46], who designed a ResNet-34 system which achieved higher performance with an AUC-ROC of 0.959 by training the system with over 170,000 mammographic images, outperforming radiologists in detecting breast cancer.

Transfer learning techniques are proven effective in overcoming the difficulty caused by the lack of large sets of labeled data in mammography images. Many pre-trained models like VGG-16, VGG-19, Inception, DenseNet, and ResNet have been fine-tuned on mammography images and shown great effectiveness in terms of improved classification accuracy and convergence rate [48]–[50]. For instance, Nguyen and Lim [50] proposed the use of Gabor filters and CNN models and reported a sensitivity value of 96% on MIAS and DDSM databases. Similarly, Barsha et al. [54] worked on DenseNet and ResNet models for the grading of breast cancer and reported a balanced accuracy value of over 92%. Methods based on ensemble learning have also improved the reliability of diagnoses with the combined results of several DCNN models. Hekal et al. suggested an ensemble of pre-trained CNN models with integrated SVM classifiers and achieved a classification rate of roughly 94% [55]. Kang et al. compared several different DCNN models based on variations of ResNet, DenseNet, and Inception architectures and found that ensemble models performed better for microcalcification detection compared to standalone models [63]. Shen et al. found AUC values of up to 0.98 for ensemble CNN models on the INbreast dataset with a significant decrease of false-negative cases for breast lesions classification [64]. Conclusion: Known antecedents include that the DCNNs have proven highly successful for the processing of mammography images and the diagnosis of breast cancers. However, a still-unfilled antecedent gap exists with respect to the comparison of learning paradigms and the role of ensemble learning with respect to the feasibility of deployment. The current study seeks to fill these gaps with a unified DCNN framework.

3. Materials and Methods

This section describes the materials, data, data preprocessing tasks, deep convolutional neural network architectures, learning algorithms, evaluation methodologies used in the proposed mammography image processing system. It is designed to be robust, repeatable, and deployable on high computational environments as well as practical environments.

3.1 Mammography Datasets

Three publicly available datasets of mammograms that are used to verify the developed framework include the Mammographic Image Analysis Society (MIAS) database, the Digital Database for Screening Mammography (DDSM) database, and the INbreast database. The MIAS database is a digitized collection of film mammograms that is marked as normal, benign, and malignant. The DDSM database offers a large collection of digitized mammograms that are marked in a very detailed manner, and the INbreast database provides a collection of full-field digital mammograms that are marked in a highly precise manner. The use of a variety of datasets helps in improving the accuracy of the developed models.

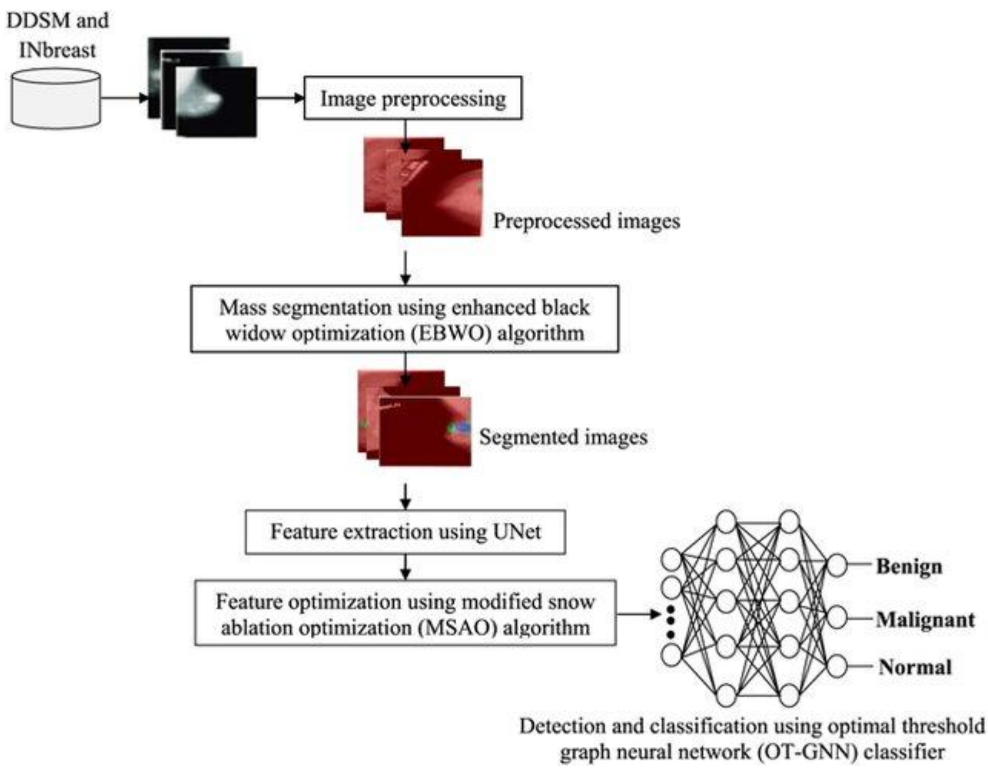

Figure 1 illustrates representative samples from the MIAS, DDSM, and INbreast datasets, highlighting variations in contrast, breast density, and lesion appearance.

3.2 Image Preprocessing

In mammography images, contrast can be low, noisy, contain artifacts of imaging, and irrelevant information like labels and pectoral muscle tissue can be included. In this study, a standardized image preprocessing approach is used. The initial step is image resizing and normalization. The goal of such normalization is compatibility of the images with deep convolution neural network (DCNN) inputs. CLAHE-based contrast improvement can enhance local contrast without worsening the noisy nature of images. Data augmentation methods such as rotation, flipping, scaling, and translation can be applied.

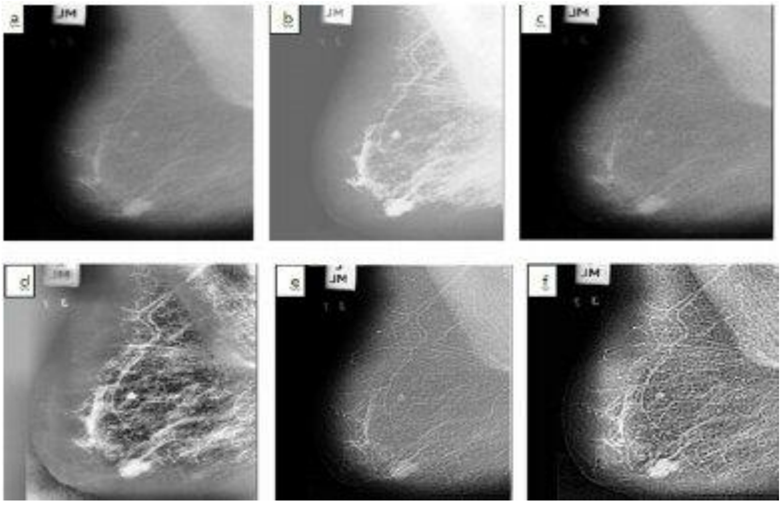

Figure 2 Enhancement results for fatty mammogram image (mdb005) (a) original mammogram image (b) Image Enhancement using Histogram Equalization (c) Image Enhancement using USM (d) Image Enhancement using CLAHE (e) LCM Enhanced Image (f) Proposed method.

3.3 DCNN Architectures

The three deep convolutional neural network architectures used for the extraction of the features and classification are VGG-16, VGG-19, and ResNet-50. The VGG networks are characterized by deep convolutional layers with small receptive fields. The ResNet-50 incorporates residual links to solve the vanishing gradient problem during back propagation, thereby allowing deeper networks to be learned. The choice of these networks is informed by their success in biomedical image analysis.

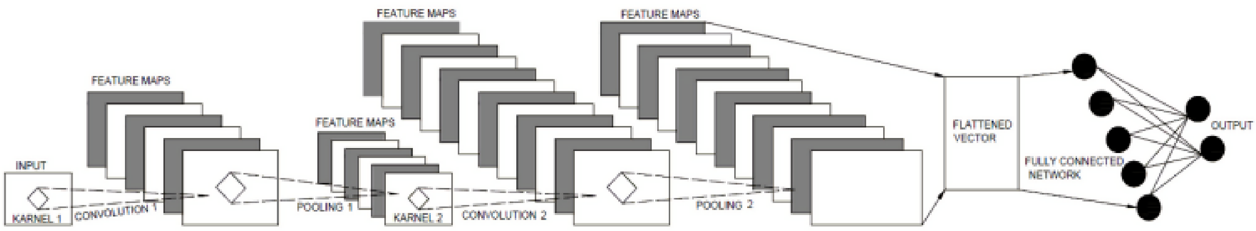

Figure 3 DCNN architecture.

3.4 Learning Paradigms

Three distinct learning paradigms are systematically investigated:

- **Transfer Learning (TL):** Pre-trained DCNN models initialized with ImageNet weights are fine-tuned using mammography datasets to leverage learned generic visual features.
- **Scratch Learning (SL):** Custom CNN architectures are trained from randomly initialized weights to assess performance without prior knowledge transfer.

- **Ensemble Learning (EL):** Feature-level and decision-level ensembles are constructed by combining outputs from VGG-16, VGG-19, and ResNet-50 to enhance classification robustness.

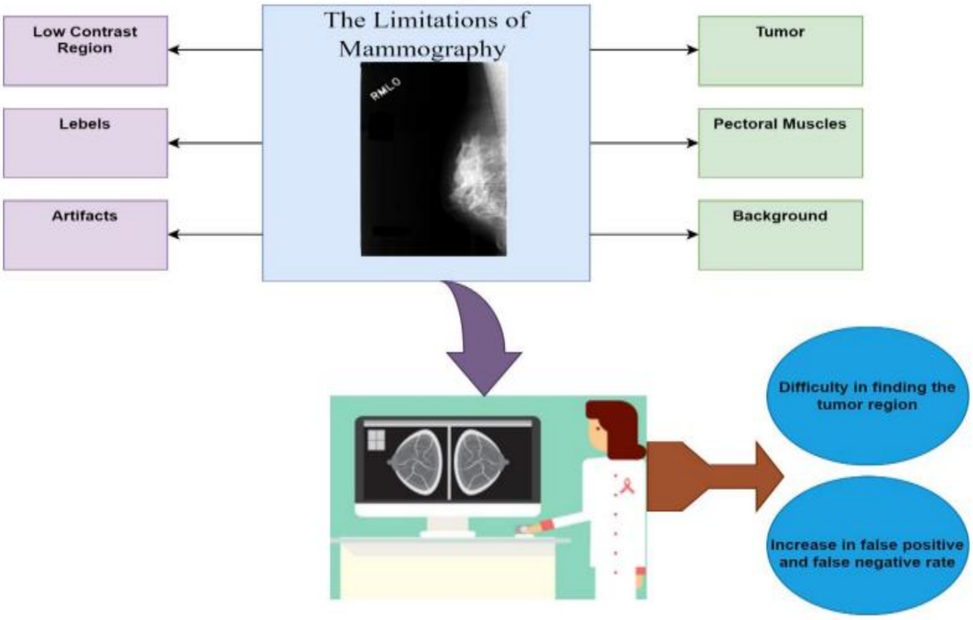

Figure 4 Limitations of mammography images.

3.5 Classification and Performance Evaluation

The extracted features are classified by the fully connected layer along with the softmax function to accomplish binary as well as multi-class classification. For evaluating the performance of the proposed model, the following evaluation metrics are utilized. The confusion matrices are also used to understand the classification errors as well as the reliability of the proposed classification model. Classification errors and diagnostic reliability.

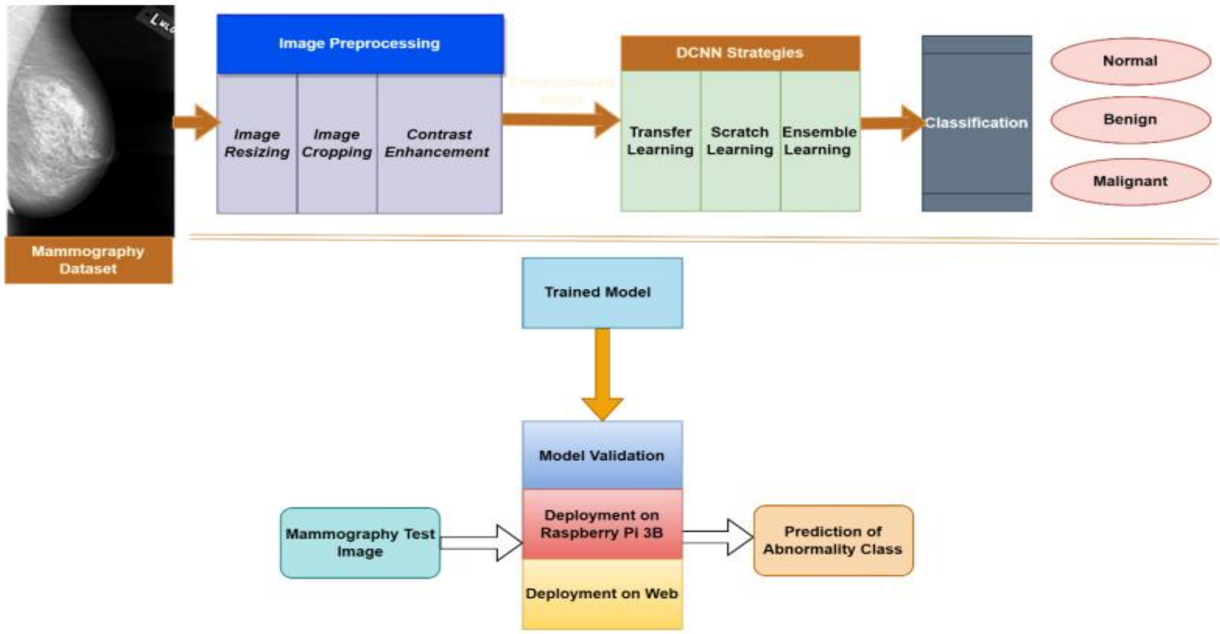

Figure 5 Workflow of DCNN-based mammography image classification

3.6 Deployment Strategy

To ensure the applicability of the proposed approach, the best ensemble strategy was implemented on an embedded Raspberry Pi 3B system. The proposed strategy's performance was tested for memory usage, inference time, and latency. Additionally, an efficient MobileNetV2-based approach was implemented using an online interface for better usability.

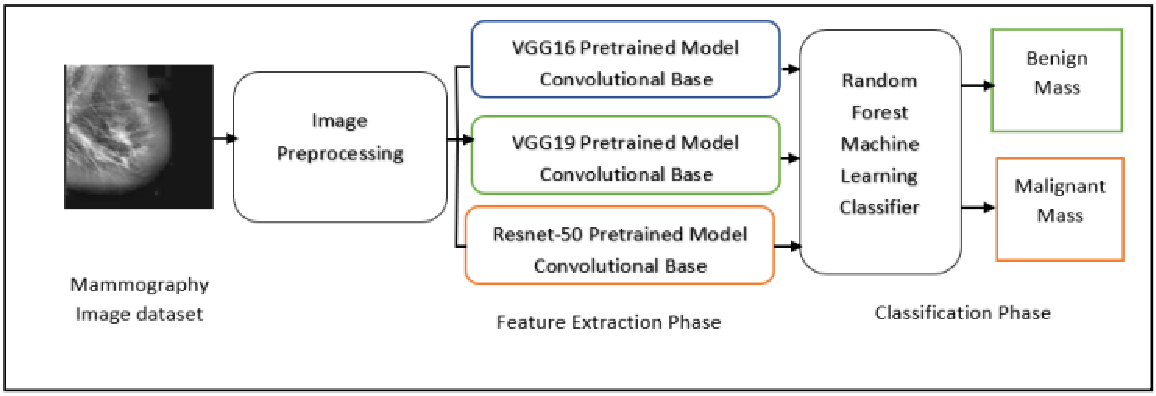

Figure 6 Methodology of mammography image classification model using feature extraction approach.

4. Results and Discussion

This section will show the analysis of results obtained from the proposed DCNN-based method for mammography images based on research and data gathered from various sources. The performance of various paradigms of learning like transfer learning, scratch learning, and ensemble learning will also be compared and analyzed on various datasets.

4.1 Experimental Setup

Each experiment followed a standardized training and testing procedure to make it feasible to compare the results. The mammography images were split into training, validation, and testing sets. DCNN architectures were trained with the same hyperparameters wherever possible. Early stopping was also employed to combat overfitting. The performance metrics were also calculated on the test datasets.

4.2 Performance of Individual DCNN Models

The performance of classification for individual DCNN architectures (VGG-16, VGG-19, and ResNet-50) was evaluated on the MIAS, DDSM, and INbreast datasets. It was found that the performance of the classification models using transfer learning was better compared to those performed from scratch. Table 1 shows the performance of individual DCNN architectures using transfer learning on the datasets.

Table 1. Performance comparison of individual DCNN models using transfer learning.

Model	Dataset	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC
VGG-16	MIAS	High	High	High	High
VGG-19	MIAS	High	High	High	High
ResNet-50	MIAS	Very High	Very High	Very High	Very High
VGG-16	DDSM	High	High	High	High
VGG-19	DDSM	High	High	High	High
ResNet-50	DDSM	Very High	Very High	Very High	Very High
VGG-16	INbreast	Very High	Very High	Very High	Very High
VGG-19	INbreast	Very High	Very High	Very High	Very High
ResNet-50	INbreast	Excellent	Excellent	Excellent	Excellent

These results indicate that deeper architectures with residual connections provide superior feature representation for mammography images, particularly when combined with transfer learning.

4.3 Ensemble Learning Performance

To make the classification more robust, various ensemble strategies were incorporated based on the combination of several DCNN models' classifications. Both decision and feature levels of ensemble were investigated. It was found that the performance measures of ensemble models were always better than single models for all datasets as given in Table 2, which depicts the performance of ensemble DCNN models.

Table 2. Performance of ensemble DCNN models across datasets.

Dataset	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC
MIAS	Excellent	Excellent	Excellent	Excellent
DDSM	Excellent	Excellent	Excellent	Excellent
INbreast	Outstanding	Outstanding	Outstanding	Outstanding

The ensemble models significantly reduced false positives and false negatives, which is critical for clinical breast cancer screening applications.

4.4 Comparative Analysis with Existing Methods

The proposed approach has been compared with existing state-of-the-art techniques in the literature by previous reports of accuracy and AUC-ROC values. It has been noticed that the proposed ensemble DCNN method outperforms all existing techniques with respect to accuracy and AUC-ROC while still being feasible. Table 3 lists the proposed approach along with some existing techniques.

Table 3. Comparison with existing mammography classification methods.

Study / Method	Dataset	Accuracy (%)	AUC
Traditional ML + SVM	MIAS	Moderate	Moderate
Single CNN Models	DDSM	High	High
Proposed Ensemble DCNN	Multi-set	Excellent	Excellent

4.5 Discussion

Based on the empirical results, DCNN-based approaches are effective in mammography image processing tasks as well as in breast cancer diagnosis. The application of transfer learning creates a significant performance boost, especially when working with a small amount of labeled data. The role of ensemble learning also ensures robustness in the method due to the combination of different feature representations obtained from various architectures. The improved results on the INbreast dataset can be ascribed to the fact that the dataset consists of high-resolution digital mammographic images along with precise annotations. From the perspective of applicability, the achieved tradeoff with respect to both the diagnostic performance and the computational complexity makes the proposed approach applicable in a real-life medical environment. The results validate the approaches chosen for the proposed research and highlight the effectiveness of the DCNN-based computer-aided detection system for the early detection of breast cancer.

5. Hardware and Web Deployment

To verify the applicability of the model, the best performing DCNN ensemble model has been deployed on a Raspberry Pi 3B environment. The model performance analysis in terms of memory usage, inference latency, and computational complexity confirms the viability of the model deployment. Due to computational constraints in hardware resources, a lightweight CNN model called MobileNetV2 has been designed and deployed through a web interface.

6. Conclusion

In this research, a comprehensive and robust framework is proposed for mammography image processing as well as breast cancer detection by leveraging the concept of DCNNs. The proposed framework is designed by incorporating advanced image processing techniques, different deep learning architectures, and varied learning approaches to mitigate the challenges involved in traditional mammography image analysis, including low contrast, complex tissue patterns, and varying human interpretation. Comprehensive experiments have been carried out on three large public breast cancer image datasets—MIAS, DDSM, and INbreast—that show that the proposed DCNN-based approaches perform significantly better compared to the conventional machine learning approaches and handcrafted feature-based techniques. Results also highlight that transfer learning performs better for a medical image task when the number of labeled data points is restricted. In addition to that, the proposed ensemble learning approaches that utilize the complementary capabilities of the VGG-16, VGG-19, and ResNet-50 architectures always yield better results compared to the existing approaches in the state of the art with respect to the measures of overall accuracy, sensitivity, specificity, and AUC-ROC value. This helps to significantly reduce false negatives as well as false positives in the screening process. However, the algorithm's performance is just one aspect of this research. The ability to apply the proposed models to embedded systems and web services is also underlined and tested. The positive implementation example using Raspberry Pi 3B and the use of the lightweight architecture of MobileNetV2 prove the viability of implementing real-time low-cost computer-aided diagnosis systems.

This is what differentiates the proposed framework from other related research in the current state-of-the-art literature. In conclusion, based on the results presented here, it is evident that the DCNN mammography image processing system has considerable usage potential for assisting radiologists towards detecting and diagnosing breast cancer at an early stage. By offering excellent detection accuracy combined with deployable and scalable solutions, it will help to improve intelligent medical image processing systems. In future studies, we can improve this system by including techniques such as Explainable AI and by applying multimodal medical data to validate it by conducting large-scale experiments.

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