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Automated Breast Cancer Detection Using Optimized CNN Models on Mammography Images: A Deep Learning Approach for Enhanced Diagnostic Accuracy

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ABSTRACT

Breast cancer is among the most common and increasing illnesses worldwide; this disease is primarily seen in women. Early identification is key to managing and controlling breast cancer. However, many previous deep learning models for breast cancer detection suffer from overfitting, poor generalization across diverse clinical cases, and reliance on limited public datasets. In this study, a deep learning model based on a custom Convolutional Neural Networks (CNNs) architecture is developed to automatically classify mammography images into normal or abnormal categories. The model was implemented using the Keras API with TensorFlow as the backend. To overcome existing limitations, key parameters such as learning rate and dropout were optimized to reduce overfitting and enhance classification performance. Various data augmentation techniques, including flipping, rotation, and contrast adjustments, were applied to improve generalization across different cases. The dataset, collected from the hospital, includes images from 430 patients across different age groups, ensuring clinical relevance. After training and evaluation, the model achieved a high accuracy of 98%, along with high sensitivity, specificity, and precision,

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confirming its reliability in distinguishing between normal and abnormal breast tissue. Compared to previous studies, this approach demonstrates competitive and, in many cases, improved classification performance. The promising outcomes indicate that the proposed CNN model has the potential to assist radiologists in identifying abnormal cases more accurately and could be a valuable tool in computer-aided diagnosis (CAD) systems for breast cancer screening.

1. Introduction

Breast cancer remains one of the most prevalent and life-threatening diseases worldwide, with an estimated 2.3 million new cases diagnosed annually, making it a significant global health concern (https://www.who.int/health-topics/breast-cancer, 2023). Early detection is a critical factor in improving survival rates, as timely diagnosis allows for effective treatment intervention and better patient outcomes.(Tiwari et al., 2020).

Cancer tumors form when cells grow abnormally and invade surrounding tissues in the human body. Tumors are classified into two types benign and malignant, and a tumor-free breast is considered normal. Benign tumor cells are non-cancerous cells that grow locally and cannot spread through invasion. While malignant tumors are cancerous cells, they can multiply uncontrollably, spread throughout the body, and invade surrounding tissue (Hamed et al., 2020).

Mammography has been widely recognized as the gold standard for breast cancer screening, providing radiologists with detailed images of breast tissue to detect abnormalities at an early stage(Kavitha et al., 2022).

Mammograms are specialized x-rays that are utilized to examine breast tissue. A specialized device equipped with two plates is used for this purpose. This device is distinguished from conventional x-ray machines in that it employs lower levels of radiation. Mammography can expedite the early detection of breast cancer, frequently before the identification of any symptoms that suggest the presence of the disease by medical professionals. This allows for early detection of breast cancer, Improving treatment outcomes (Salh & Ali, 2023). However, manual interpretation of mammograms heavily depends on radiologist expertise, which can lead to inconsistent diagnoses and interpretation errors. Studies show that misdiagnosis rates can reach 30%, especially in dense breast tissue (Hirra et al., 2021).

To address this, many healthcare institutions have adopted Computer-Aided Detection (CAD) systems. CAD systems assist radiologists by improving diagnostic precision and reducing errors. In 1998, the U.S. Food and Drug Administration (FDA) authorized the commercial release of CAD after determining its valid and dependable performance. The tool has gained universal acceptance for breast cancer screening at medical institutions worldwide. (Jasti et al., 2022).

The present CAD systems use manually designed feature extraction methods, including texture analysis and shape detection, for the identification of potential lesions in mammograms. These methodologies are non-adjustable and generate improper positive and negative results, particularly for challenging medical cases. Modern CAD systems fight these limitations by implementing Convolutional Neural Networks (CNNs) and deep learning methods(Raza et al., 2021).

CNN-based models have shown excellent performance in breast cancer detection by capturing critical image patterns without manual intervention. CNN-based models demonstrate superior classification accuracy by adapting to different tumor appearances because they overcome traditional machine learning requirements for manually created features (Yaqub et al., 2024). Deep learning technology serves as a strong analytical tool for mammograms since it provides both better radiologist-independent diagnosis and enhanced reliability (Aljuaid et al., 2022). Recent advancements in deep learning for breast cancer diagnosis include ensemble learning, attention-based networks, and segmentation-aware CNNs, all contributing to improved classification accuracy and lesion localization. However, many existing studies still depend heavily on public datasets and lack clinical validation, highlighting the ongoing need for models tailored to real-world hospital data.

This study proposes a Convolutional Neural Network (CNN) based classification model, for classifying normal and abnormal cases from mammography images. This

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research sets itself apart from previous studies through the following key contributions:

- Custom A custom-designed CNN architecture was optimized specifically for binary classification (normal vs abnormal) of mammography images, demonstrating strong capability in distinguishing between the two classes.
- Adaptive learning rate tuning and dropout regularization strategies to enhance model generalization and reduce overfitting.
- Extensive data augmentation techniques were applied to improve robustness across different imaging conditions.
- A clinically collected dataset from Hospital was used, ensuring practical relevance beyond public datasets.

The remainder of this paper is structured as follows. The next section provides a comprehensive review of related work, discussing recent advancements in deep learning for breast cancer classifications. This is followed by a description of the dataset, preprocessing techniques, and augmentation methods used to improve model performance. The subsequent section details the proposed methodology, including the architectures of CNN model. The experimental setup, training procedures, and results obtained from model evaluation are then presented, followed by a discussion of key findings. Finally, the study concludes with a summary of contributions, limitations, and future research directions.

2.Related Works

Deep learning technology for breast cancer detection has experienced rapid advancements in recent years, driven by researchers' efforts to develop improved detection techniques through innovative network designs, ensemble methods, and transfer learning approaches. Multiple convolutional neural network (CNN) models have been studied to optimize detection results in different mammography datasets via unique optimization approaches. Deep learning models, particularly convolutional neural networks (CNNs), have been widely employed in breast cancer diagnosis to enhance the accuracy and reliability of mammography analysis. These models reduce the need for manually crafted features by autonomously extracting spatial and texture-based components from mammographic images. Numerous

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studies have employed end-to-end designs that learn directly from image data without relying on radiologist-annotated regions of interest. Certain models, for instance, focus on binary classification—normal versus abnormal—while others pursue multi-class classification, such as distinguishing between benign and malignant, or differentiating among masses and microcalcifications. Utilizing knowledge from general image classification tasks has been employed to address limited dataset sizes through transfer learning with pretrained models such as ResNet, InceptionV3, and VGGNet. Other works integrate techniques like segmentation, ensemble learning, or feature fusion to improve diagnostic precision.

One of the earliest advancements in this domain was introduced by (Shen et al., 2019) who developed an end-to-end deep learning model using an all-convolutional network. Their system trained on CBIS-DDSM and INbreast datasets through an approach that reduced the need for specific lesion labeling to enhance its potential for large-scale breast cancer screening. Transfer learning used in clinical imaging demonstrated its capacity to improve classification accuracy and minimize classification errors through achieving accuracy at 91% and 95%. However, their multi-phase training and dependence on public datasets may increase complexity and restrict generalization in clinical environments. The scope of deep learning applications in breast cancer classification expanded when (Rashed & Samir Abou El Seoud, 2019) developed a deep learning approach using a novel CNN architecture called O-net for classifying mammographic images. They evaluated their model on the CBIS-DDSM dataset, concentrating on distinguishing between microcalcifications and masses, by extracting features from convolutional and deconvolutional layers, their model reached classification accuracy of 94.31% for microcalcifications and 95.01% for masses, demonstrating superior performance compared to earlier architectures like AlexNet and VGGNet. However, the system required manually selected ROIs for training, which limits automation and scalability in clinical environments. Building upon these developments, the research of (Alfifi et al., 2020) demonstrated the requirement for advanced feature extraction through their combination of Traditional CNN (TCNN), Supported CNN (SCNN) models with an innovation called Flipped Rotation-Based Approach (FRbA). The authors analyzed distorted images in the MIAS dataset mammograms with special attention to problems caused by shift and scaling distortions. The researchers enhanced detection accuracy through spatial transformation integration which led the SCNN model to achieve 87% accuracy while its enhanced version with FRbA reached 91% accuracy. These findings demonstrated that combining preprocessing stages with feature alignment techniques optimizes CNN-based classifier performance. Nevertheless, the study was limited to a small dataset and lacked clinical validation, which may restrict its generalizability to real-world screening environments. (Tsochatzidis et al., 2021) introduced a method that integrates segmentation maps directly into the CNN layers to improve the classification accuracy of mammographic masses. They modified each convolutional layer by integrating segmentation maps into the system which helped the model concentrate its analysis on target lesion areas. The system obtained 89.9% Accuracy on the DDSM-400 and 86,2% accuracy on the CBIS-DDSM dataset through the fusion of segmentation data within a CNN-based classification framework. On the other hand, the authors noted that segmentation map integration alone did not always improve performance and that a spatially aware loss function was needed to leverage segmentation data, limiting training stability and convergence fully. In the same year, (Khan et al., 2021) developed multi-class classification model using ResNet50. The authors distinguished this work from previous analyses which focused on binary classification by creating a model that capable of identifying masses, calcifications, asymmetry, and carcinomas when processing CBIS-DDSM and UPMC datasets. The study demonstrated an accuracy of 88%, confirming the value of detailed classification methods in enhancing medical diagnosis. Despite dropout and data augmentation, the model's generalization ability was uncertain due to limited external validation beyond its custom dataset. Additionally, the model initially overfitted severely. Additionally,(Desai & Shah, 2021) A comparative analysis was conducted between Multi-Layer Perceptron (MLP) neural networks and Convolutional Neural Networks (CNNs) for breast cancer diagnosis. The review included studies using datasets such as BreakHis, MIAS, and WBCD. CNN models consistently outperformed MLPs, achieving higher accuracy and better feature extraction for image-based classification. However, as a limitation, the comparison was based on different datasets and conditions, and a direct evaluation on the same dataset is still needed. In parallel (Lin et al., 2022) in parallel, Lin et al. (2022) investigated ensemble learning by training AlexNet, ResNet101, and InceptionV3 networks using transfer learning techniques. They utilized a small clinical mammogram dataset and a breast cancer risk factor dataset from the BCSC. While InceptionV3 independently achieved an accuracy of 91.3%, combining the models through soft-voting ensemble methods enhanced overall classification performance, reaching 94.2%. Nevertheless, the study's performance was constrained by the limited size of the mammogram dataset, increasing the risk of overfitting. The Transferable Texture Convolutional Neural Network (TTCNN) represented a new step forward when (Maqsood et al., 2022) developed the model to detect early breast cancer with digital mammograms. The

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research method consisted of multiple phases which began with contrast enhancement then proceeded with texture feature extraction and finished with feature fusion. Different benchmark models including ResNet50 and InceptionResNet-V2 and VGG16 had lower accuracy rates than the 97.49% achieved by TTCNN during tests on DDSM, INbreast and MIAS datasets. In contrast, (Sunardi et al., 2022) compared CNN and Faster R-CNN models for classifying breast cancer mammograms. Using the MIAS dataset, they assessed each model's performance in identifying normal and abnormal cases. The findings indicated that the CNN model outperformed Faster R-CNN, reaching an accuracy of 91.26%, whereas Faster R-CNN lagged at 63.89%. The study emphasized that while Faster R-CNN excels in object detection tasks, CNN models are more suitable for straightforward classification problems like distinguishing normal from abnormal cases. Lastly (Jafari & Karami, 2023) introduced a CNN-based feature selection model which combined AlexNet with ResNet50 and MobileNet with ConvNeXt as well as EfficientNet. A model processed RSNA MIAS and DDSM datasets to perform feature selection for improved accuracy which reached 96% accuracy on DDSM by using age data for patient classification.

Although previous studies have shown robust progress in breast cancer detection with deep learning, several common limitations remain in many of these studies. These challenges include relying on public datasets, not testing on clinical images, complicated designs, needing manual selection of important areas, and not performing well across different cases. While some approaches only consider binary classification, others introduce a multi-stage process lacking in applicability to real-world workflows.

To address these gaps, this study introduces a custom CNN model trained on clinically collected mammograms. The model integrates adaptive learning rate tuning, dropout regularization, and comprehensive data augmentation to enhance generalization. It provides a fully automated, efficient, and reliable pipeline for classifying normal and abnormal cases, with the potential to support early diagnosis and assist radiologists in clinical practice.

3.Dataset

Mammography techniques are classified into two types of film-screen mammography and digital mammography, also known as full-field digital mammography (FFDM). While both use similar imaging principles, film-screen mammography captures images on photographic films, whereas digital mammography records digital files on a computer. This research focuses on digital mammography, (Figure 1) which shows

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examples of both techniques. The dataset used in this study is a private clinical dataset collected from Maryamana Hospital with proper authorization. It consists of 864 mammographic images obtained from 430 patients aged between 25 and 70 years who visited the hospital's specialized breast cancer unit for routine mammography screenings. for each patient two images were included among these, 100 of those was diagnosis with cancer, 210 whom just had lumps, and 120 had normal without any lumps. The dataset was constructed with cooperation from the hospital and medical professionals and doctors, ensuring ethical considerations and clinical relevance. Each image is stored as a color image with a resolution of 512 × 512 pixels, which is the ideal size displaying for cancer images based on other rates that have been researched. The images were processed and standardized using (RadiAnt, DICOM Viewer), a widely used medical imaging software.

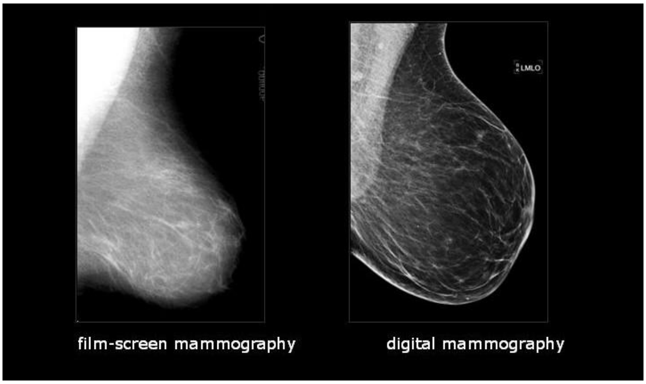

Figure 1:*Digital mammography with screen-film mammography.*

2. Material & Methodes

The main goal of this study is to create a model that effectively classifies mammography images into normal and abnormal categories. The proposed architecture is organized into three main phases. First, the mammography dataset was collected and prepared as described above. Next, the dataset goes through data augmentation and then divided into training, validation, and testing subsets. Finally, the model implementations and architecture were designed. Each of these phases is explained in detail in the following subsections.

2.1 Data augmentation algorithm (DAA)

Data augmentation is a crucial technique in deep learning that enhances model generalization by artificially increasing the size and diversity of the dataset. In this study, various augmentation strategies were applied to mammographic images to improve classification accuracy while preserving essential tumor characteristics. Different augmentation approaches applied to mammographic images for obtaining higher classification accuracy alongside maintaining critical tumor patterns. The data preprocessing applied enumerated several steps that involved batch resizing all images to 224×224 pixels together with normalization for pixel value scaling between 0 and 1 and utilization of geometric transformations including random rotations up to 20 degrees and horizontal and vertical flips as well as contrast modifications to achieve imaging condition simulation. The introduced augmentations brought various elements to the dataset which helped the model develop stronger features and avoid learning specific patterns through overfitting. The application of data augmentation on diverse breast cancer acquisitions enabled the CNN to achieve higher accuracy levels while becoming more robust and generalizable to unknown data samples thus making it critical for training trustworthy deep learning-based mammogram classification systems.

2.2 General Overview of CNN

CNNs represent the current best healthcare technology for medical image classification because they can extract complex hierarchical features from raw images without human intervention. CNN employs an architecture that differs from that of conventional neural networks, in which each layer is coordinated in terms of its width, height, and depth (Aslan, 2023). Additionally, it comprises two primary components the classification component and the hidden layers. Convolutions and pooling operations are accomplished in the hidden layer. The convolution employs several filters to extract features, and the dimensional feature maps are minimized using

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pooling. The fully connected layer is responsible for the attribution of probability and prediction for the object in the classification phase (Bahaa-Eldin, 2021).

2.3 CNN Model Implementation

Convolutional Neural Networks (CNNs) are widely recognized for their ability to automatically learn spatial hierarchies of features directly from image data, making them well-suited for medical image analysis. In the context of mammography, where identifying subtle differences in tissue patterns is critical, CNNs offer significant advantages over traditional methods that rely on handcrafted features. A custom CNN architecture was adopted in this study to provide a lightweight yet effective solution for binary classification of mammographic images. This design allows for controlled adjustment of architectural parameters such as filter sizes, depth, and dropout rates, which is particularly important for optimizing performance and ensuring efficient learning. The CNN serves as the primary component of the classification framework, extracting relevant features through convolutional layers and enabling robust discrimination between normal and abnormal breast tissue.

In this study, we developed a lightweight Convolutional Neural Network (CNN) optimized for the binary classification of mammography images into normal and abnormal categories. The architecture consists of three convolutional layers that are shown in figure (2), each followed by MaxPooling layers, designed to extract essential image features while reducing spatial dimensions and computational complexity. The first convolutional layer contains 32 filters of size 3×3, followed by a second layer with 64 filters (3×3) and a third convolutional layer with 128 filters (3×3). Each convolutional operation applies the ReLU activation function, ensuring non-linearity and improved feature learning. MaxPooling layers (2×2 kernel size) follow each convolutional layer to downsample feature maps and retain critical spatial information. To mitigate overfitting, Dropout regularization is applied after the pooling layers. The dropout rates progressively increase from 0.2 to 0.3 and finally to 0.4, improving the model's generalization ability. These hyperparameters were selected based on a combination of prior literature and empirical tuning during model development. The learning rate of 0.001 was found to provide stable convergence without oscillation, while the progressive dropout scheme was designed to regularize each layer appropriately and prevent overfitting. These values yielded the best trade-off between training performance and generalization during validation trials. The extracted feature maps are then flattened into a one-dimensional vector and passed through a fully connected dense layer with 128 neurons, which further refines the learned representations. The final classification is performed using a sigmoid-activated dense layer, which outputs a probability score for the binary classification task. The model is compiled using the Adam optimizer with a learning rate of 0.001, ensuring adaptive learning and stable convergence. The binary cross-entropy loss function is used to minimize classification errors and improve predictive performance. During training, the model achieved a training accuracy of 96% and a validation accuracy of 98%, demonstrating high reliability and robustness in mammogram classification. Given its low computational requirements, the proposed CNN model is well-suited for mammography image analysis, particularly in computer-aided breast cancer detection.

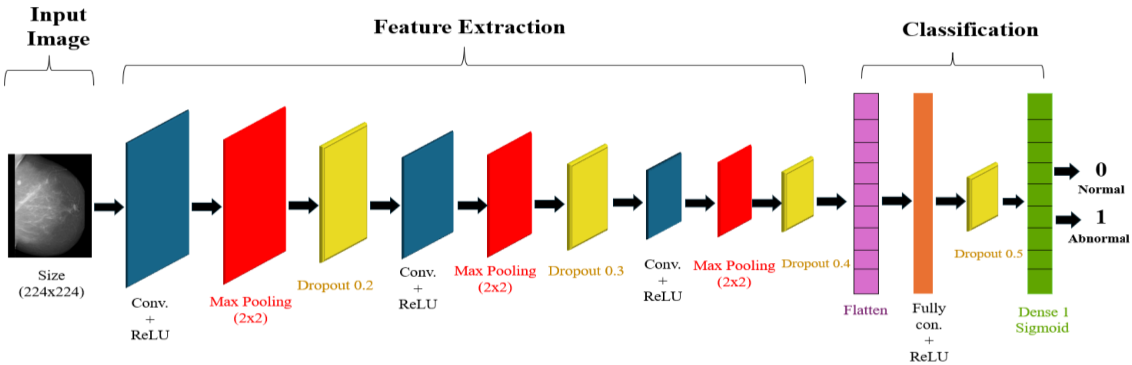

Figure 2: *Custom CNN-based deep learning architecture.*

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3. Experimental Setup

All experiments in this study were implemented using Python 3.11.3 and executed in the Visual Studio Code (VS Code) environment. The development of the model utilized the Keras 3.8.0 API through TensorFlow version 2.18.0 as its backend framework. The OpenCV library conducted all required image preprocessing processes, including resizing, normalization, and augmentation. The mammography dataset was split into three subsets: 80% for training, 10% for validation, utilized for tuning the model parameters and monitoring overfitting during training, and 10% for evaluating the dataset (unseen data) for model assessment. The data augmentation techniques helped the model achieve better generalization capabilities. First, professional doctors labelled the mammography images as normal and abnormal, and these labels were used to train the proposed CNN model to extract key features from images to distinguish between normal and abnormal breast tissues, and to enable accurate classifications. The training process employed 50 epochs through which the model learned its parameters using a learning rate (0.001) while working with a batch size (32). The model was trained on a CPU using Visual Studio Code, completing all epochs in approximately one hour (72 seconds per epoch), demonstrating feasible performance without GPU acceleration, The results and the testing of each experiment will be discussed in detail.

4. Results and Discussion

In This work a Convolutional Neural Network (CNN) model was constructed to identify and separate the test cases of mammogram images into 'normal' and 'abnormal' categories. The dataset used in this work was obtained from the Hospital, and utilized for system training, validation, and testing. The model was designed to provide high classification results that are satisfactory, aiming to improve the accuracy in the early detection of breast cancer. The proposed model was evaluated based on the classification results which are shown in Table (1). The evaluation measures demonstrated robust performance, achieving high true positive (TP) rate, precision, sensitivity, specificity, and F1-score, confirming the power of the model. The model performs excellently for both normal and abnormal cases, with minimal cases of

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misclassification as illustrated by the confusion matrix in Figure 3. Additionally, Figures 4 and 5 shows the Receiver Operating Characteristic (ROC) curve and Precision-Recall (PR) curve which depict the capabilities of the model to sustain the robust tradeoff between true positive (TP) rates and false positive (FP) rates. These results are additional evidence of the strength of our model.

The standard performance measures used for evaluating the model include accuracy rate (AC), precision rate (PR), sensitivity (SE), specificity (SP), and F1 score (FS). Each metric is computed based on true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), as mathematically defined in equations (1) too (5).

The experimental results, supported by Figures 6 and 7, confirm the efficiency and reliability of the proposed method, indicating its potential to assist radiologists in clinical breast cancer screening.

1. $Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)}$

2. $Sensitivity = \frac{TP}{(TP+FN)}$

3. $precision = \frac{TP}{(TP+FP)}$

4. $F - Score = \frac{(2\times Precision\times Sensitivity\ )}{Precision\times Sensitivity}$

5. $Specificity = \frac{TN}{(TN+FP)}$

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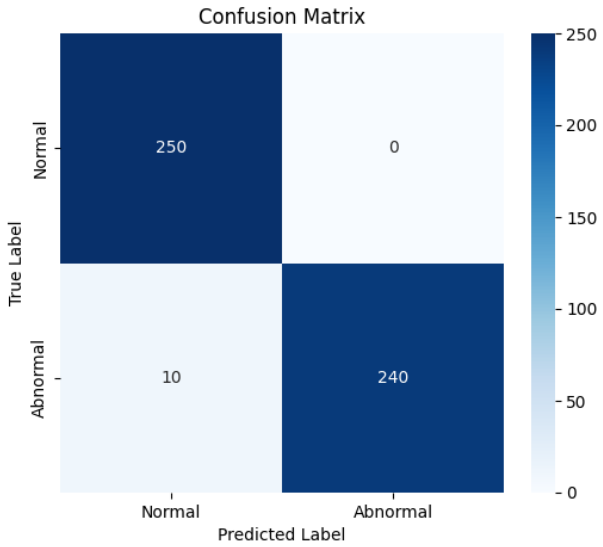

Figure 3: *Confusion matrix classification results*

Figure (4) Mean receiver operating characteristic (ROC) analysis results on the entire dataset using the proposed CNN model. The ROC curve achieved an area under the curve (AUC) of 0.99, indicating excellent discrimination capability between normal and abnormal mammography images. The total training time was approximately 1 hour.

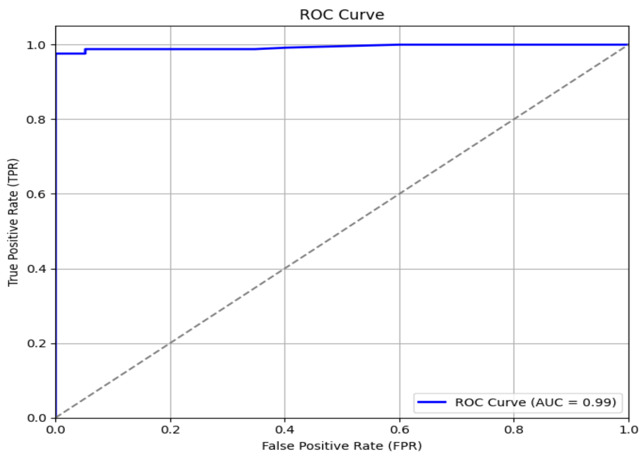

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Figure 4: *Area under the curve (0.99) by using CNN model.*

The classification performance of the proposed CNN model on the test dataset is summarized in Table 1. The test set was not used during training or validation, ensuring an objective assessment of the model's generalization ability.

Table 1*: Breast cancer classification performance of CNN model for normal and abnormal:*

Class	Sensitivity	Precision	Specificity	F1-Score	Accuracy
Normal	1.00	0.96	1.00	0.98	0.98
Abnormal	0.96	1.00	0.96	0.98	0.98

Figure (5) presents the Precision-Recall analysis results obtained from the test dataset using the proposed CNN model. The curve demonstrates the model's strong ability to distinguish between normal and abnormal mammography images. Precision remained consistently high across most recall thresholds, reaching 1.00 for a large portion of the curve, which reflects the absence of false positives. The model also maintained a recall close to 96%, confirming its reliability in identifying abnormal cases with high confidence.

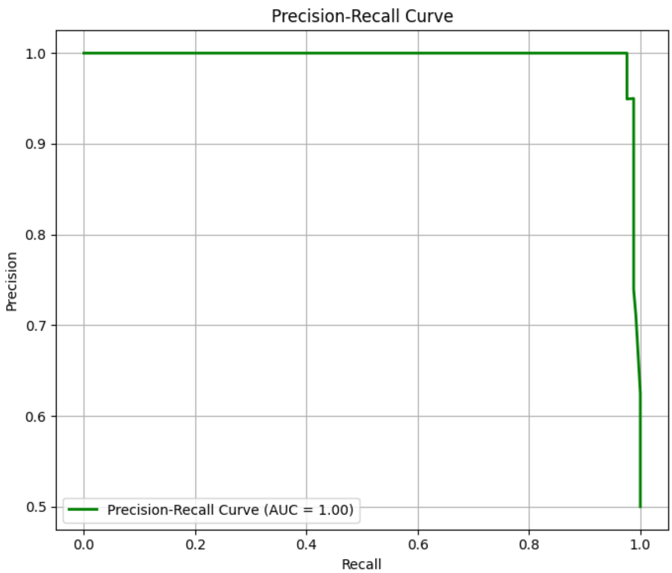

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Figure (6) illustrates the training and validation accuracy progression of our proposed CNN model over 50 epochs. Throughout the training, both accuracy curves consistently increased, reflecting effective learning and model stability. The model achieved approximately 96% training accuracy, while the validation accuracy reached a peak of 98%, indicating strong generalization capability without overfitting.

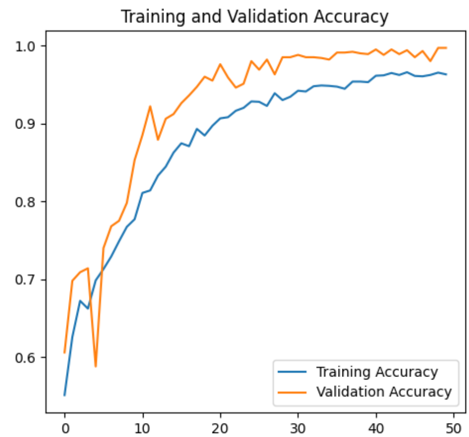

Figure 6: *Training/validation accuracies vs. Number of epochs (CNN)*

Figure (7) demonstrates the training and validation loss curves of the CNN model over 50 epochs. The loss consistently decreased for training and validation sets, indicating effective model learning. and at the end of training, the validation loss reached approximately 0.02, while the training loss stabilized around 0.1. The steady reduction of loss without significant divergence between the two curves confirms that the model is well-optimized and not overfitting

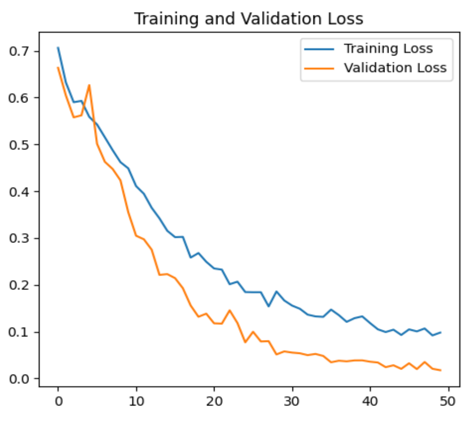

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Figure 7: *Training/validation loss vs. Number of epochs (CNN)*

The performance of our proposed model has been evaluated against several existing approaches from previous studies. Table 2 presents a comparative analysis conducted by considering factors such as methodology, dataset characteristics, and achieved results. The comparison clearly indicates that our model demonstrates superior accuracy and efficiency in classifying mammography images, establishing it as a reliable approach for breast cancer detection.

Table 2: *Performance Comparison of the Proposed CNN Model with Five Methods for Breast Cancer Diagnosis Using*

Ref	Methodology	Datasets	Proposed Method	Result
(Shen et al., 2019)	CNN	CBIS-DDSM, INbreast	Classification (Normal vs Abnormal)	91% 95%
(Khan et al., 2021)	Resnet50, CNN	CBIS-DDSM	Multi-Class Classification – Identified specific types of abnormalities.	88%
(Alfifi et al., 2020)	TCNN, SCNN, FRbA	MIAS	Classification (Normal, Benign, Malignant)	83%, 87%, 91%
(Sunardi et al., 2022)	CNN, Faster R-CNN	MIAS	Classification (Normal vs Abnormal)	91.26% 63.89%
(Jafari & Karami, 2023)	Feature Concatenation from AlexNet, ResNet50, MobileNet, ConvNeXt, EfficientNet	RSNA, MIAS, DDSM	Classification Normal vs Abnormal, using multi-model feature extraction.	94.5% (MIAS), 96% (DDSM), 92% (RSNA)
Proposed Methode	Custom CNN model	Collected the primary mammogram images from Maryamana Hospital	Classification (Normal vs Abnormal)	98%

As presented in Table 2, the proposed CNN model achieved superior classification accuracy compared to a range of previously reported methods. While existing models report performance between 88% and 96%, the proposed method achieved 98% accuracy on clinically collected mammography images. Unlike many prior studies that rely on public datasets, this model was validated using real-world clinical data, enhancing its practical relevance. Notably, radiologist sensitivity in interpreting mammograms has been reported to range from 67% to 91%, depending on factors such as experience and breast density (Lehman et al., 2017). With a sensitivity of 96% and a precision of 100%, the proposed model demonstrates strong potential to assist radiologists by reducing diagnostic variability and supporting more consistent, reliable decision-making in breast cancer screening.

5. Conclusion

The Interpretation of Mammograms through manual methods is often time-consuming and susceptible to human error, highlighting the need for reliable automated diagnostic tools. This study addressed these challenges by developing a custom Convolutional Neural Network (CNN)-based model for classifying mammography images into normal and abnormal categories. The proposed model achieved 98% classification accuracy, outperforming previous studies using optimized learning rates, data augmentation techniques, and dropout regularization. Experimental results demonstrate the model’s ability to automatically extract essential features from mammographic data, reducing errors associated with manual interpretation and enhancing diagnostic reliability. The model has the potential to improve patient outcomes in breast cancer care by reducing diagnostic delays and supporting clinical workflows.

Despite the promising results, some limitations must be acknowledged. The dataset used in this research was collected from a single institution, which may limit the model's generalizability. External validation on larger, multi-institutional datasets is needed to further confirm robustness. To support broader clinical adoption, practitioners may consider integrating such lightweight CNN models into existing computer-aided diagnosis (CAD) systems, particularly in settings with limited access to expert radiologists. Future research should explore interpretability frameworks such as Grad-CAM to enhance model transparency and assess performance across diverse populations. Techniques like federated learning and semi-supervised training may also improve scalability and preserve data privacy in clinical deployments.

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دۆزینەوەی شێرپەنجەی مەمک بە شێوەیەکی ئۆتۆماتیکی بە بەکارهێنانی مۆدێلی باشکراوی CNN لەسەر وێنەکانی مەمۆگرافی: ڕێبازێکی فێربوونی قووڵ بۆ باشترکردنی وردی دەستنیشانکردن

پـوختـە:

شێرپەنجەی مەمک لە باوترین و زیادبوونی نەخۆشییەکانە لە سەرانسەری جیهاندا؛ ئەم نەخۆشییە بە شێوەیەکی سەرەکی لە ئافرەتاندا دەبینرێت. دەستنیشانکردنی پێشوەختە کلیلی بەڕێوەبردن و کۆنترۆڵکردنی شێرپەنجەی مەمکە. بەڵام، زۆرێک لە مۆدێلەکانی پێشووی فێربوونی قووڵ بۆ دیاریکردنی شێرپەنجەی مەمک بەدەست زیادەگونجاندن، گشتاندنی خراپ لە سەرانسەری حاڵەتە کلینیکییە جیاوازەکاندا، و پشتبەستن بە کۆمەڵە داتا گشتییە سنووردارەکان دەناڵێنن. لەم توێژینەوەیەدا ، مۆدێلێکی فێربوونی قووڵ لەسەر بنەمای بیناسازی تۆڕە دەمارییە پێچاوپێچەکانی تایبەتمەند (CNNs) پەرەی پێدراوە بۆ ئەوەی وێنەکانی مەمۆگرافی بە شێوەیەکی ئۆتۆماتیکی پۆلێن بکرێت بۆ پۆلە ئاساییەکان یان نائاساییەکان. مۆدێلەکە بە بەکارهێنانی Keras API جێبەجێ کرا لەگەڵ TensorFlow وەکو پاشکۆ. بۆ زاڵبوون بەسەر سنووردارکردنی ئێستا، پارامێتەرەکانی سەرەکی وەک ڕێژەی فێربوون و وازهێنان لە خوێندن باشتر کران بۆ کەمکردنەوەی زیادەگونجاندن و بەرزکردنەوەی ئەدای پۆلێنکردن. تەکنیکە جیاوازەکانی زیادکردنی داتا، لەوانەش وەرچەرخان، خولانەوەی و ڕێکخستنی کۆنتراست، بەکارهێنران بۆ باشترکردنی گشتاندن لە سەرانسەری حاڵەتە جیاوازەکاندا. ئەو کۆمەڵە زانیارییە کە لە نەخۆشخانەوە کۆکراوەتەوە، وێنەی 430 نەخۆش لەخۆدەگرێت لە سەرانسەری گروپە تەمەنییە جیاوازەکاندا، ئەمەش دڵنیای دەدات لە پەیوەندی کلینیکی. دوای ڕاهێنان و هەڵسەنگاندن، مۆدێلەکە وردبینییەکی بەرزی 98% بەدەستهێنا، لەگەڵ هەستیاری و تایبەتمەندی و وردبینی بەرز، ئەمەش متمانەپێکراوی خۆی لە جیاکردنەوەی نێوان شانە ئاسایی و نائاساییەکانی مەمکدا پشتڕاستکردەوە. بە بەراورد لەگەڵ توێژینەوەکانی پێشوو، ئەم ڕێبازە کێبڕکێ و لە زۆر حاڵەتدا باشتربوونی ئەدای پۆلێنکردن نیشان دەدات. دەرەنجامە ئومێدبەخشەکان ئاماژە بەوە دەکەن کە مۆدێلی پێشنیارکراوی CNN توانای یارمەتیدانی پزیشکانی تیشکی هەیە لە

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ناسینەوەی حاڵەتە نائاساییەکان بە وردی و دەتوانێت ئامرازێکی بەنرخ بێت لە سیستەمی دەستنیشانکردنی بە یارمەتی کۆمپیوتەر (CAD) بۆ سکرینکردنی شێرپەنجەی مەمک..

الكشف الآلي عن سرطان الثدي باستخدام نماذج CNN المُحسّنة على صور التصوير الشعاعي للثدي: نهج التعلم العميق لتحسين دقة التشخيص

الملخص:
سرطان الثدي من أكثر الأمراض شيوعًا وانتشارًا في جميع أنحاء العالم؛ ويُلاحظ هذا المرض بشكل أساسي لدى النساء. يُعدّ الكشف المبكر أمرًا أساسيًا لإدارة سرطان الثدي والسيطرة عليه. ومع ذلك، تعاني العديد من نماذج التعلم العميق السابقة للكشف عن سرطان الثدي من الإفراط في التجهيز، وضعف التعميم عبر الحالات السريرية المتنوعة، والاعتماد على مجموعات بيانات عامة محدودة. في هذه الدراسة، طُوّر نموذج تعلم عميق قائم على بنية شبكات عصبية تلافيفية مخصصة (CNNs) لتصنيف صور تصوير الثدي بالأشعة السينية تلقائيًا إلى فئات طبيعية أو غير طبيعية. طُبّق النموذج باستخدام واجهة برمجة تطبيقات Keras مع TensorFlow كواجهة خلفية. وللتغلب على القيود الحالية، تم تحسين المعلمات الرئيسية مثل معدل التعلم والتسرب لتقليل الإفراط في التجهيز وتحسين أداء التصنيف. طُبّقت تقنيات مختلفة لزيادة البيانات، بما في ذلك التقليب والتدوير وتعديلات التباين، لتحسين التعميم عبر الحالات المختلفة. تتضمن مجموعة البيانات، التي جُمعت من المستشفى، صورًا من 430 مريضًا من مختلف الفئات العمرية، مما يضمن الصلة السريرية. بعد التدريب والتقييم، حقق النموذج دقة عالية بلغت 98%، بالإضافة إلى حساسية وخصوصية ودقة عالية، مما يؤكد موثوقيته في التمييز بين أنسجة الثدي الطبيعية وغير الطبيعية. وبالمقارنة مع الدراسات السابقة، يُظهر هذا النهج أداءً تنافسيًا، بل ومُحسّنًا في كثير من الحالات، في التصنيف. وتشير النتائج الواعدة إلى أن نموذج CNN المُقترح لديه القدرة على مساعدة أخصائيي الأشعة في تحديد الحالات غير الطبيعية بدقة أكبر، ويمكن أن يكون أداة قيّمة في أنظمة التشخيص بمساعدة الحاسوب (CAD) لفحص سرطان الثدي.