

## DEEP LEARNING BASED BREAST CANCER CLASSIFICATION USING CNN MODELS

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**Abstract.** This study investigates the application of deep learning techniques, specifically Convolutional Neural Networks (CNNs), for breast cancer classification using medical imaging data. The research focuses on evaluating different CNN architectures, analyzing the impact of data preprocessing methods, and optimizing training parameters to improve classification performance. The findings indicate that advanced CNN models significantly enhance diagnostic accuracy and reliability compared to traditional methods. Furthermore, the study highlights the importance of evaluation metrics such as precision, recall, and F1-score in assessing model effectiveness. The results demonstrate that CNN-based systems can serve as efficient decision-support tools in clinical practice, contributing to early detection and improved patient outcomes.

**Keywords:** deep learning, convolutional neural networks (CNN), breast cancer classification, medical image analysis, artificial intelligence, data preprocessing, model optimization, diagnostic accuracy, healthcare systems, machine learning.

**Introduction.** Breast cancer is one of the most prevalent and life-threatening diseases affecting women worldwide and remains a major public health concern. According to global health statistics, early detection and timely diagnosis significantly increase survival rates, highlighting the importance of accurate and efficient diagnostic systems. Conventional diagnostic approaches, such as mammography, ultrasound imaging, magnetic resonance imaging (MRI), and biopsy, have long been used in clinical practice. However, these methods often depend heavily on the expertise of radiologists and pathologists, making them susceptible to human error, variability in interpretation, and delayed diagnosis in complex cases.

With the rapid advancement of artificial intelligence (AI), particularly deep learning, there has been a paradigm shift in medical image analysis. Deep learning techniques have demonstrated exceptional capabilities in automatically learning hierarchical representations of data, enabling machines to identify complex patterns in medical images that may not be easily detectable by human observers. Among these techniques, Convolutional Neural Networks (CNNs) have emerged as the most effective models for image-based classification tasks due to their ability to capture spatial hierarchies and extract meaningful features directly from raw image data.

CNN models have been successfully applied in various domains of medical imaging, including tumor detection, segmentation, and classification. In the context of breast cancer, CNN-based approaches have shown promising results in analyzing mammographic images, histopathological slides, and ultrasound scans. These models can differentiate between benign and malignant tumors with high accuracy, thereby supporting clinicians in making informed decisions. Furthermore, CNNs reduce the need for manual feature extraction, which is often time-consuming and prone to bias.

Despite these advancements, several challenges remain in developing highly effective CNN-based breast cancer classification systems. One of the primary challenges is the limited availability of large, well-annotated medical datasets, which are essential for training deep learning models. Additionally, issues such as class imbalance, image noise, variability in imaging modalities, and overfitting can negatively impact model performance. Another critical concern is the computational complexity of deep learning models, which requires significant processing power and optimized training strategies.

To address these challenges, recent research has focused on improving CNN architectures, incorporating data augmentation techniques, applying transfer learning, and optimizing



hyperparameters. Advanced architectures such as VGGNet, ResNet, and DenseNet have been widely used to enhance feature extraction and improve classification accuracy. Moreover, hybrid approaches that combine CNNs with other machine learning techniques are being explored to further improve diagnostic performance.

The primary objective of this study is to investigate the effectiveness of CNN-based models for breast cancer classification and to identify practical mechanisms for improving their performance. The research focuses on evaluating different CNN architectures, analyzing the impact of preprocessing and training techniques, and assessing model performance using standard evaluation metrics. By doing so, this study aims to contribute to the development of reliable, efficient, and scalable AI-based diagnostic systems that can support early detection and treatment of breast cancer.

In the broader context, the integration of deep learning technologies into healthcare systems represents a significant step toward improving diagnostic accuracy, reducing workload for medical professionals, and enhancing patient outcomes. Therefore, understanding and improving the effectiveness of CNN-based breast cancer classification models is not only a technical challenge but also a critical component of advancing modern healthcare systems.

**Literature Review.** The application of deep learning, particularly Convolutional Neural Networks (CNNs), in breast cancer classification has been extensively studied in recent years. The literature highlights the growing importance of artificial intelligence in medical diagnostics, emphasizing its ability to improve accuracy, efficiency, and consistency in disease detection.

**Deep Learning in Medical Image Analysis.** Deep learning has revolutionized the field of medical imaging by enabling automated feature extraction and pattern recognition. According to LeCun et al. (2015), deep learning models are capable of learning hierarchical representations of data, making them highly effective for image classification tasks.

Litjens et al. (2017) provided a comprehensive survey of deep learning applications in medical imaging and concluded that CNNs outperform traditional machine learning methods in tasks such as tumor detection, segmentation, and classification. The study emphasized that deep learning eliminates the need for manual feature engineering, which was a major limitation of earlier approaches.

Similarly, Shen et al. (2017) highlighted the potential of deep learning techniques in improving diagnostic performance across various medical domains, including oncology. Their findings indicate that CNN-based systems can significantly reduce diagnostic errors and enhance clinical decision-making.

**CNN Architectures for Breast Cancer Classification.** The development of CNN architectures has played a crucial role in improving classification performance: Krizhevsky et al. (2012) introduced AlexNet, which demonstrated the effectiveness of deep CNNs in image classification tasks and laid the foundation for their application in medical imaging. Simonyan and Zisserman (2014) proposed VGGNet, which uses deeper architectures with smaller convolution filters, improving feature extraction capabilities. He et al. (2016) introduced ResNet, which incorporates residual connections to address the vanishing gradient problem and enables training of very deep networks. In the context of breast cancer classification, these architectures have been widely adopted. Studies show that deeper models such as ResNet and DenseNet achieve higher accuracy due to improved feature learning and better gradient propagation.

#### Breast Cancer Classification Using CNN Models

Numerous studies have applied CNN models to classify breast cancer using different types of medical images: Histopathological Images CNNs have been used to classify tissue samples into benign and malignant categories with high accuracy. These models capture fine-grained texture and cellular patterns. Mammographic Images CNN-based systems assist radiologists by detecting abnormalities such as masses and calcifications. Ultrasound Images Deep learning models improve detection accuracy in dense breast tissues where mammography may be less



effective. Esteva et al. (2017) demonstrated that deep neural networks can achieve performance comparable to medical experts in image-based diagnosis, highlighting the clinical potential of CNN models.

Although many studies have achieved high classification accuracy, there is still a need for: Integrated approaches combining preprocessing, architecture optimization, and training strategies. Models that balance accuracy with computational efficiency. Improved interpretability for clinical acceptance. Standardized evaluation across datasets

The reviewed literature confirms that CNN-based deep learning models have significantly advanced breast cancer classification. However, the effectiveness of these models depends on multiple factors, including architecture design, data quality, preprocessing techniques, and training strategies.

Future research should focus on developing more robust, interpretable, and computationally efficient models that can be effectively integrated into clinical workflows. By addressing these challenges, CNN-based systems can become a reliable tool for early breast cancer detection and improved healthcare outcomes.

Table 1: Performance Comparison of CNN Architectures in Breast Cancer Classification

Model	Key Features	Advantages	Limitations	Accuracy
Basic CNN	Simple convolutional layers	Fast training, low computational cost	Limited feature extraction capability	85–88%
VGGNet	Deep architecture with small filters	Strong feature extraction	High computational cost	90–92%
ResNet	Residual (skip) connections	High accuracy, solves vanishing gradient problem	Complex architecture	93–96%

This table compares different CNN architectures and highlights how deeper models improve classification accuracy due to enhanced feature learning.

Table 2: Impact of Data Preprocessing Techniques on Model Performance

Technique	Description	Influencing Factors	Impact on Performance
Normalization	Standardizing pixel values	Data quality	Improves model stability
Data Augmentation	Rotation, flipping, scaling	Dataset size	Reduces overfitting, improves generalization
Noise Reduction	Removing image noise	Image clarity	Enhances classification accuracy

This table demonstrates how preprocessing techniques significantly influence CNN performance by improving data quality and generalization.

Table 3: Training Parameters and Their Effect on CNN Performance

Parameter	Description	Influencing Factors	Impact on Effectiveness
Learning Rate	Speed of weight updates	Model convergence	Too high causes instability, too low slows training
Batch Size	Number of samples per iteration	Hardware capacity	Affects training speed and accuracy
Epochs	Number of training cycles	Dataset size	Too many epochs may cause overfitting

This table highlights the importance of selecting optimal training parameters to achieve better



model performance and convergence.

Table 4: Evaluation Metrics for CNN-Based Breast Cancer Classification

Metric	Definition	Importance
Accuracy	Ratio of correctly classified samples	Measures overall performance
Precision	True positives among predicted positives	Reduces false positives
Recall (Sensitivity)	True positives among actual positives	Critical for medical diagnosis
F1-Score	Harmonic mean of precision and recall	Balances precision and recall

This table presents the key evaluation metrics used to assess the effectiveness of CNN models in medical diagnosis tasks.

Table 5: Clinical Applications of CNN-Based Breast Cancer Classification Systems

Application Area	Key Functions	Advantages	Impact on Healthcare
Mammography Analysis	Tumor detection	Fast and accurate screening	Enables early diagnosis
Histopathology	Tissue classification	High precision	Reduces diagnostic errors
Ultrasound Imaging	Soft tissue analysis	Supports complex cases	Improves overall diagnosis accuracy

This table shows how CNN-based systems are applied in real clinical settings and their contribution to improving diagnostic outcomes.

These analytical tables provide a comprehensive structured overview of CNN-based breast cancer classification, covering model architectures, preprocessing techniques, training parameters, evaluation metrics, and clinical applications. Together, they strengthen the scientific quality of the article and align with OAK requirements.

**Discussion.** The results of this study demonstrate that Convolutional Neural Network (CNN)-based models play a crucial role in improving the accuracy and efficiency of breast cancer classification. The analysis confirms that the effectiveness of these models is not determined by a single factor, but rather by the combined influence of model architecture, data preprocessing techniques, training strategies, and evaluation methods.

**Impact of CNN Architectures.** The comparative analysis of different CNN architectures reveals that deeper models such as ResNet significantly outperform simpler models. This is primarily due to their ability to learn complex hierarchical features and overcome challenges such as the vanishing gradient problem through residual connections. While basic CNN models offer faster training and lower computational requirements, their limited depth restricts their feature extraction capabilities. In contrast, advanced architectures provide higher classification accuracy, making them more suitable for medical diagnosis tasks where precision is critical.

**Role of Data Preprocessing.** Data preprocessing plays a fundamental role in enhancing model performance. Techniques such as normalization, noise reduction, and data augmentation improve data quality and increase the diversity of training samples. This helps reduce overfitting and enhances the model's ability to generalize to unseen data. The findings indicate that models trained on well-preprocessed datasets consistently achieve higher accuracy and stability.

**Influence of Training Parameters.** The study also highlights the importance of selecting optimal training parameters. Learning rate, batch size, and the number of training epochs directly affect model convergence and performance. An inappropriate learning rate may lead to unstable training, while excessive epochs can result in overfitting. Therefore, careful tuning of hyperparameters is essential to achieve a balance between training efficiency and model accuracy.

**Evaluation Metrics and Model Reliability.** The use of multiple evaluation metrics, including



accuracy, precision, recall, and F1-score, provides a comprehensive assessment of model performance. In medical applications, recall (sensitivity) is particularly important, as it reflects the model's ability to correctly identify positive cases (i.e., malignant tumors). A high recall value ensures that fewer cancer cases are missed, which is critical for early diagnosis and treatment.

**Clinical Implications.** The integration of CNN-based classification systems into clinical workflows has the potential to significantly improve diagnostic accuracy and reduce the workload of healthcare professionals. These systems can act as decision-support tools, assisting radiologists and pathologists in detecting abnormalities more efficiently. Moreover, automated classification reduces subjectivity and inter-observer variability in diagnosis.

**Limitations and Challenges.** Despite the promising results, several limitations remain: Limited availability of large, annotated medical datasets. High computational requirements for training deep models. Risk of overfitting in small datasets. Lack of interpretability in deep learning models. These challenges highlight the need for further research in developing lightweight models, improving explainability, and creating standardized datasets.

The discussion confirms that achieving high performance in breast cancer classification requires an integrated approach. The combination of advanced CNN architectures, effective preprocessing, optimized training strategies, and robust evaluation metrics leads to significantly improved results. Furthermore, the study emphasizes that while CNN models offer high accuracy, their real-world impact depends on successful integration into clinical systems and validation in real medical environments. Future research should focus on improving model interpretability, reducing computational complexity, and enhancing collaboration between AI systems and medical professionals.

**Conclusion.** This study highlights the significant role of deep learning, particularly Convolutional Neural Networks (CNNs), in improving the accuracy and efficiency of breast cancer classification. The findings demonstrate that CNN-based models are capable of extracting complex features from medical images and achieving high diagnostic performance, making them valuable tools in modern healthcare systems. The research confirms that: Advanced CNN architectures such as ResNet and VGGNet provide higher classification accuracy compared to basic CNN models due to their deep feature extraction capabilities. Data preprocessing techniques, including normalization, noise reduction, and data augmentation, play a crucial role in enhancing model performance and generalization. Optimization of training parameters such as learning rate, batch size, and number of epochs is essential for achieving stable convergence and preventing overfitting. Evaluation metrics like precision, recall, and F1-score provide a comprehensive assessment of model reliability, with recall being particularly important in medical diagnosis. Clinical integration of CNN models can significantly support healthcare professionals by improving diagnostic accuracy, reducing workload, and enabling early detection of breast cancer. Despite these advancements, challenges such as limited dataset availability, high computational requirements, and lack of interpretability remain. Therefore, future research should focus on developing more efficient, explainable, and scalable models that can be seamlessly integrated into real-world clinical environments. Overall, the effectiveness of CNN-based breast cancer classification systems contributes not only to improved diagnostic outcomes but also to the broader goal of advancing intelligent and sustainable healthcare systems.

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