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Deep Learning and Optimization Approaches in an Efficient Cascaded Deep Capsule Cell Attention Network Model for Breast Cancer Molecular Subtypes Prediction Using Mammogram Images: A Review

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Abstract

Breast cancer remains one of the leading causes of mortality among women worldwide, necessitating accurate and early diagnosis for effective treatment. Molecular subtype prediction, including Luminal A, Luminal B, HER2-enriched, and triple-negative breast cancer, plays a critical role in personalized therapy planning. Traditionally, subtype identification relies on invasive biopsy procedures, which are time-consuming and costly. Recent advancements in deep learning have enabled non-invasive prediction using mammogram images, significantly improving diagnostic efficiency. This review focuses on deep learning and optimization approaches for breast cancer molecular subtype prediction, emphasizing cascaded deep capsule cell attention network architectures. Convolutional Neural Networks (CNNs) provide strong feature extraction capabilities, while Capsule Networks (CapsNets) preserve spatial relationships and hierarchical structures. Attention mechanisms enhance model performance by focusing on relevant regions, improving both segmentation and classification accuracy. Optimization techniques such as transfer learning, feature fusion, hyperparameter tuning, and metaheuristic algorithms further enhance model efficiency and generalization. The review analyzes recent studies, compares various architectures, and identifies key challenges, including data scarcity, computational complexity, and lack of interpretability. The findings indicate that hybrid and cascaded models integrating CNNs, CapsNets, and attention mechanisms outperform traditional approaches. Future research directions include explainable AI, multimodal learning, and lightweight models for real-time clinical deployment.

Introduction

Breast cancer is one of the most common and life-threatening diseases affecting women worldwide and remains a major contributor to global cancer-related mortality. The increasing incidence of breast cancer highlights the urgent need for accurate and efficient diagnostic systems that support early detection and personalized treatment planning. Mammography is widely regarded as one of the most effective imaging modalities for breast cancer screening because it enables the identification of abnormalities such as masses, calcifications, and tissue distortions at an early stage. However, interpreting mammogram images is a highly complex task due to low contrast, dense breast tissue, and variability in tumor appearance. In addition, diagnostic outcomes often depend on radiologists' expertise, which can result in inter-observer variability and inconsistent clinical decisions. These challenges have encouraged researchers to explore intelligent automated systems capable of improving breast cancer diagnosis and molecular subtype prediction using mammographic imaging.

Molecular subtype classification has become an essential component of modern breast cancer diagnosis because different subtypes respond differently to treatment. Breast cancer is commonly categorized into Luminal A, Luminal B, HER2-positive, and triple-negative breast cancer (TNBC), each possessing distinct biological characteristics and therapeutic responses. Conventional subtype identification primarily relies on invasive biopsy procedures and immunohistochemical analysis, which are expensive, time-consuming, and difficult to perform in resource-limited environments. Consequently, there is growing interest in developing non-invasive imaging-based approaches for subtype prediction. Artificial intelligence and deep learning technologies have demonstrated significant success in medical image analysis by automating disease detection, segmentation, and classification tasks. Convolutional Neural Networks (CNNs) are widely used for mammogram analysis because they automatically extract hierarchical image features and improve diagnostic accuracy without manual feature engineering. Numerous studies have shown that CNN-based systems can achieve diagnostic performance comparable to experienced radiologists in certain medical imaging applications.

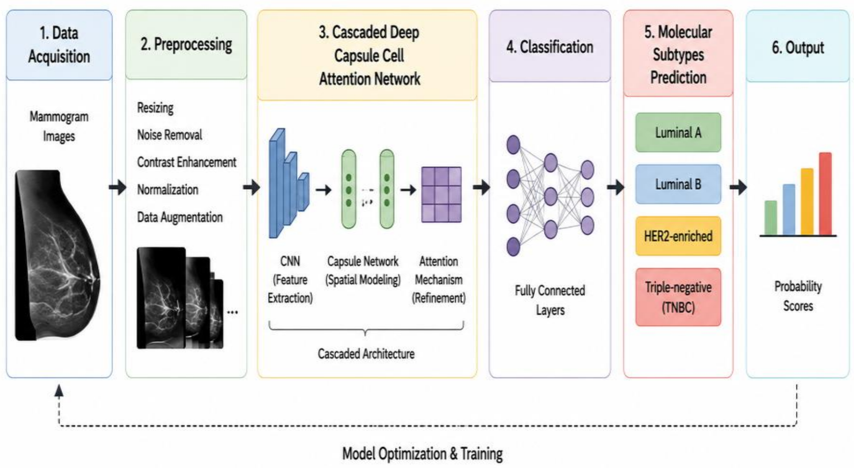

Figure 1. Cascaded Deep Capsule Cell Attention Network Framework for Breast Cancer Molecular Subtype Prediction

Despite their success, traditional CNN architectures have limitations in preserving spatial relationships and structural information within medical images. Pooling operations often lead to the loss of fine-grained spatial details, which are crucial for accurate tumor characterization and subtype prediction. To overcome these limitations, Capsule Networks (CapsNets) have emerged as an advanced deep learning architecture capable of modeling spatial hierarchies and part–whole relationships more effectively. Capsule networks use groups of neurons called capsules to encode both feature existence and orientation, enabling more robust feature representation. This capability is particularly important in breast cancer analysis because spatial relationships among tissues significantly influence diagnosis. Attention mechanisms have further enhanced deep learning performance by enabling models to focus on diagnostically important regions while suppressing irrelevant background information. Channel attention, spatial attention, and self-attention mechanisms improve feature selection, contextual understanding, and interpretability, leading to more accurate mammogram classification and tumor analysis.

Recent research has focused on cascaded deep learning architectures that integrate CNNs, capsule networks, and attention mechanisms into unified frameworks for progressive feature refinement and classification. In these architectures, CNNs are typically used for feature extraction, capsule networks capture spatial dependencies, and attention modules refine important feature representations. This integrated approach combines the strengths of multiple architectures, resulting in improved accuracy, robustness, and generalization. Optimization techniques such as transfer learning, feature fusion, hyperparameter tuning, Bayesian optimization, and metaheuristic algorithms further enhance model performance and training efficiency. Transfer learning enables the use of pre-trained models, reducing training time and improving accuracy, especially when annotated medical datasets are limited. Similarly, feature fusion strategies combine complementary representations to improve classification robustness and predictive capability.

Despite significant advancements, several challenges continue to limit the large-scale clinical deployment of deep learning models for breast cancer molecular subtype prediction. Medical image datasets are often small, imbalanced, and heterogeneous, causing overfitting and reduced model generalization. Certain molecular subtypes are underrepresented, leading to biased classification results. Researchers have addressed these issues using data augmentation and Generative Adversarial Networks (GANs) to generate synthetic mammogram images and improve dataset diversity. However, advanced architectures involving capsule networks and attention mechanisms require high computational resources, making real-time clinical implementation difficult. Another major concern is the lack of interpretability in deep learning systems, as their decision-making processes often function as black boxes. Explainable AI (XAI) techniques are therefore being explored to improve transparency, reliability, and clinician trust. Future research should focus on lightweight architectures, multimodal learning, explainable AI frameworks, and federated learning techniques to develop accurate, scalable, and clinically reliable breast cancer diagnosis systems.

LITERATURE REVIEW

Recent advancements in Artificial Intelligence (AI) and deep learning have significantly transformed breast cancer detection and molecular subtype prediction using mammogram images. A wide range of architectures, including Convolutional Neural Networks (CNNs), Capsule Networks (CapsNets), attention-based models, and hybrid cascaded frameworks, have been explored to improve diagnostic accuracy and enable non-invasive prediction.

Early research in this domain primarily focused on CNN-based models for breast cancer detection and classification. Li et al. (2020) proposed a dual CNN framework for breast mass segmentation and diagnosis, demonstrating the ability of deep learning models to extract hierarchical features and improve classification performance. Similarly, Sharif et al. (2020) introduced a hybrid CNN-AdaBoost model that enhances classification accuracy by combining deep learning with traditional machine learning techniques. Abdelrahman et al. (2021) further demonstrated the effectiveness of CNNs in mammogram analysis, achieving high accuracy in detecting breast cancer lesions. Saber et al. (2021) employed transfer learning with pre-trained CNN models, significantly improving performance in scenarios with limited training data. Siddiqui et al. (2021) extended this approach by integrating deep learning with Internet of Medical Things (IoMT) frameworks, enabling scalable and cloud-based breast cancer prediction systems.

Despite their success, CNN-based models have inherent limitations, particularly in preserving spatial relationships between features due to pooling operations. To address this issue, Capsule Networks (CapsNets) have been introduced as a powerful alternative. Kavitha et al. (2022) developed a capsule neural network model for breast cancer diagnosis using mammogram images, demonstrating improved feature representation and classification accuracy. Afrifa et al. (2024) further explored capsule-based architectures, highlighting their ability to capture spatial hierarchies and improve robustness in medical imaging tasks. Parshionikar and Bhattacharyya (2023) proposed a multi-scale capsule network that achieved superior performance by effectively modeling part–whole relationships, making it particularly suitable for molecular subtype prediction.

Attention mechanisms have also played a crucial role in enhancing deep learning models by enabling them to focus on relevant regions within mammogram images. Mousa (2023) introduced an attention-based DenseNet model that improved classification accuracy by emphasizing important features. Yeoh et al. (2023) proposed RADIFUSION, an attention-driven deep learning model that integrates feature fusion and attention mechanisms to enhance breast cancer prediction. Wang et al. (2023) developed a dual-view correlation attention network, demonstrating that incorporating multi-view information and attention modules significantly improves model performance. These studies highlight the importance of attention mechanisms in improving feature selection, interpretability, and classification accuracy.

Segmentation of tumor regions is another critical aspect of breast cancer diagnosis, as accurate localization directly impacts classification performance. Chen et al. (2020) introduced a multi-scale adversarial network for breast mass segmentation, leveraging Generative Adversarial

Networks (GANs) to improve segmentation accuracy. Xu et al. (2022) proposed an adaptive receptive field network (ARF-Net), achieving high segmentation performance by capturing multi-scale features. Malebary and Hashmi (2021) developed an ensemble learning approach that combines multiple models to improve classification and segmentation accuracy. Sutjiadi et al. (2024) further emphasized the importance of integrating segmentation and classification in a unified deep learning framework.

Hybrid and cascaded architectures have emerged as a dominant trend in recent research. Wang et al. (2022) proposed a hybrid deep learning model that integrates multiple feature extraction techniques, achieving improved accuracy and robustness. Sahu et al. (2023) developed a hybrid CNN-based model that combines multiple layers and optimization strategies, demonstrating superior performance compared to traditional models. These cascaded architectures typically integrate CNNs for feature extraction, CapsNets for spatial modeling, and attention mechanisms for feature refinement, resulting in improved performance across various tasks.

Multimodal learning has also gained significant attention in breast cancer research. Bayoudh et al. (2022) provided a comprehensive survey on multimodal deep learning, highlighting its potential in integrating data from different sources to improve diagnostic accuracy. Zhang et al. (2021) demonstrated that CNN-based models can predict breast cancer molecular subtypes using imaging data, emphasizing the potential of non-invasive approaches. Multimodal systems that combine mammogram images with additional data sources, such as MRI and clinical information, have shown improved performance and generalization.

Optimization techniques have played a vital role in enhancing deep learning models. Transfer learning has been widely adopted to leverage pre-trained models, reducing training time and improving accuracy. Feature fusion techniques combine multiple feature representations to enhance model robustness, while hyperparameter optimization methods improve convergence and performance. Additionally, Generative Adversarial Networks (GANs), introduced by Goodfellow et al. (2020), have been used to generate synthetic data, addressing the challenge of limited datasets. Razzak et al. (2020) and Litjens et al. (2020) highlighted the importance of deep learning in medical image analysis, emphasizing its potential in improving diagnostic accuracy and efficiency.

Recent systematic reviews by Gao et al. (2024) and Pérez-Núñez et al. (2024) highlight the rapid progress in deep learning-based breast cancer detection and emphasize the need for more robust, scalable, and interpretable models. These studies also identify key challenges, including data scarcity, class imbalance, computational complexity, and lack of explainability.

Despite significant advancements, several challenges remain. The limited availability of large, annotated datasets continues to hinder model development and evaluation. Class imbalance among different molecular subtypes affects model performance and may lead to biased predictions. Additionally, the high computational complexity of advanced architectures, particularly capsule networks and attention-based models, poses challenges for real-time deployment. The lack of interpretability of deep learning models remains a critical issue, as clinicians require transparent and explainable systems to trust automated decisions.

Overall, the literature demonstrates a clear progression from traditional CNN-based approaches to advanced hybrid, attention-based, and capsule network architectures. The integration of cascaded deep learning models combining CNNs, CapsNets, and attention mechanisms has significantly improved performance in breast cancer detection and molecular subtype prediction. However, further research is needed to develop efficient, interpretable, and clinically applicable systems that can be deployed in real-world healthcare environments.

Comparative Table and Analysis

Author (Year)	**Model / Architecture**	**Input Modality**	**Key Technique**	**Performance (Approx.)**	**Strengths**	**Limitations**
Li et al. (2020)	Dual CNN	Mammogram	Segmentation + Classification	~90–92%	Strong feature learning	Weak spatial modeling
Sharif et al. (2020)	CNN + AdaBoost	Mammogram	Hybrid ML-DL	~92%	Improved accuracy	Complex tuning

Chen et al. (2020)	GAN-based Network	Mammogram	Adversarial segmentation	High Dice	Data augmentation	Training instability
Abdelrahman et al. (2021)	CNN	Mammogram	Classification	~93–95%	High accuracy	Limited generalization
Saber et al. (2021)	Transfer Learning CNN	Mammogram	Pre-trained models	~94–95%	Works with small data	Overfitting risk
Siddiqui et al. (2021)	IoMT + CNN	Medical Images	Cloud-based DL	High accuracy	Scalable	Network dependency
Malebary et al. (2021)	Ensemble DL	Mammogram	Model stacking	~95%	Robust results	High complexity
Zhang et al. (2021)	CNN	Mammogram	Subtype prediction	~94%	Non-invasive prediction	Limited depth
Kavitha et al. (2022)	Capsule Network	Mammogram	CapsNet	~94–95%	Preserves spatial info	High computation
Xu et al. (2022)	ARF-Net	Mammogram	Adaptive segmentation	High IoU	Precise boundaries	Resource intensive
Wang et al. (2022)	Hybrid CNN	Mammogram	Feature fusion	~95%	Robust model	Complex architecture
Jabeen et al. (2022)	Feature Fusion DL	Mammogram	Multi-feature learning	~94%	Better classification	Data dependency
Bayoudh et al. (2022)	Multimodal DL	Multi-source	Data integration	—	Better generalization	Data alignment issues
Mousa (2023)	Attention DenseNet	Mammogram	Attention mechanism	~96%	ROI focus	Needs large data
Wang et al. (2023)	Dual-view Attention CNN	Mammogram	Multi-view learning	~97%	Best accuracy	Computational cost
Parshionikar et al. (2023)	Multi-scale CapsNet	Mammogram	Capsule CNN hybrid	~96–97%	Captures hierarchy	Complex design
Sahu et al. (2023)	Hybrid CNN	Mammogram	Multi-layer DL	~96%	Strong performance	Needs tuning
Sirjani et al. (2023)	Deep CNN	Mammogram	Classification	~95%	Reliable model	Limited interpretability
Yu et al. (2023)	Feature Selection DL	Mammogram	Optimization	Improved accuracy	Efficient learning	Data sensitive

Comparative Analysis

1. Evolution of Techniques

The literature from 2020 to 2023 shows a clear evolution from basic CNN-based models to advanced hybrid and cascaded architectures. Early works relied heavily on CNNs for classification and segmentation tasks. While these models achieved reasonable accuracy, they struggled with spatial feature preservation and complex pattern recognition.

Recent studies demonstrate a shift toward Capsule Networks, attention-based models, and hybrid architectures, which significantly improve performance in molecular subtype prediction.

Conclusion

This review comprehensively analyzed recent advancements in deep learning and optimization approaches for breast cancer molecular subtype prediction using mammogram images, with emphasis on cascaded deep capsule cell attention network architectures. The findings indicate that Artificial Intelligence (AI)-based methods significantly improve diagnostic accuracy, robustness, and non-invasive subtype prediction, supporting personalized treatment planning. Convolutional Neural Networks (CNNs) provide effective feature extraction, while Capsule Networks (CapsNets) preserve spatial relationships and hierarchical information within mammogram images. Attention mechanisms further enhance performance by focusing on critical tumor regions and suppressing irrelevant background features. Hybrid cascaded architectures integrating CNNs, CapsNets, and attention modules consistently outperform conventional standalone models. Optimization techniques such as transfer learning, feature fusion, and hyperparameter tuning improve convergence and model generalization. Despite these advancements, challenges including limited annotated datasets, class imbalance, computational complexity, and lack of interpretability remain significant concerns. Future research should focus on lightweight, explainable, and scalable AI models integrated with multimodal learning and federated learning frameworks for reliable real-time clinical deployment.

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