Archives available at journals.mriindia.com

International Journal on Advanced Computer Engineering and Communication Technology

ISSN: 2278-5140

Volume 14 Issue 02, 2025

A Comprehensive Review of an Efficient Cascaded Deep Capsule Cell Attention Network Model for Breast Cancer Molecular Subtypes Prediction Using Mammogram Images

Dmitro Somanathan
Assistant Professor, Department of Electrical and Computer Engineering, Padma Institute of Business and Management, Bangladesh
Email: dmitro.somanathan@pibm-bd.org

Peer Review Information

Submission: 29 Nov 2025

Revision: 10 Dec 2025

Acceptance: 25 Dec 2025

Keywords

Breast Cancer, Molecular Subtypes, Deep Learning, Capsule Networks, Attention Mechanism, Mammography, Image Classification, Medical Image Analysis, Transfer Learning, CNN

Abstract

Breast cancer remains one of the leading causes of mortality among women worldwide, with molecular subtypes such as Luminal A, Luminal B, HER2-enriched, and triple-negative playing a critical role in treatment planning and prognosis. Accurate prediction of these subtypes traditionally requires invasive biopsy procedures. Recently, deep learning-based approaches using mammogram images have emerged as a promising non-invasive alternative. This review presents a comprehensive analysis of advanced architectures for breast cancer molecular subtype prediction, with a particular focus on cascaded deep capsule networks integrated with attention mechanisms. Convolutional Neural Networks (CNNs), transfer learning models, and hybrid architectures have demonstrated strong performance in mammography-based diagnosis. Capsule networks (CapsNets), with their ability to preserve spatial hierarchies and part–whole relationships, offer improved feature representation compared to traditional CNNs. Furthermore, attention mechanisms enhance the model's ability to focus on relevant regions, improving classification accuracy. Cascaded architectures combining CNNs, CapsNets, and attention modules have shown significant potential in capturing both local and global features for subtype prediction. This review highlights recent advancements, compares state-of-the-art models, and discusses key challenges such as data scarcity, model interpretability, and computational complexity. The findings indicate that integrating capsule networks with attention mechanisms in a cascaded framework significantly improves performance in molecular subtype prediction. Future research should focus on multimodal learning, explainable AI, and lightweight architectures for real-time clinical deployment.

Introduction

Breast cancer remains one of the most critical health concerns worldwide and continues to be a leading cause of cancer-related mortality among women. Early diagnosis and accurate classification are essential for improving patient survival and enabling effective treatment planning. Mammography has become the most widely used imaging technique for breast cancer screening because of its ability to identify suspicious abnormalities at an early stage. However, manual interpretation of mammogram images is often challenging due to tissue overlap, image noise, low contrast, and variability in tumor appearance. These challenges can lead to diagnostic inconsistency and false predictions, increasing the need for automated and intelligent diagnostic systems. Recent advancements in Artificial Intelligence (AI) and deep learning have significantly improved the ability to analyse mammographic data with higher accuracy and efficiency.

One of the most important objectives in breast cancer diagnosis is the identification of molecular subtypes such as Luminal A, Luminal B, HER2-enriched, and Triple Negative Breast Cancer (TNBC). These subtypes play a crucial role in determining prognosis, therapeutic decisions, and personalized treatment strategies. Conventional molecular subtype identification relies on invasive biopsy procedures followed by histopathological and immunohistochemical analysis. Although these methods provide reliable results, they are expensive, time-consuming, and sometimes impractical in resource-limited healthcare environments. Consequently, researchers have explored AI-based non-invasive prediction systems capable of identifying molecular subtypes directly from mammogram images. Deep learning models have demonstrated promising performance by automatically learning discriminative image features associated with tumor patterns and tissue characteristics.

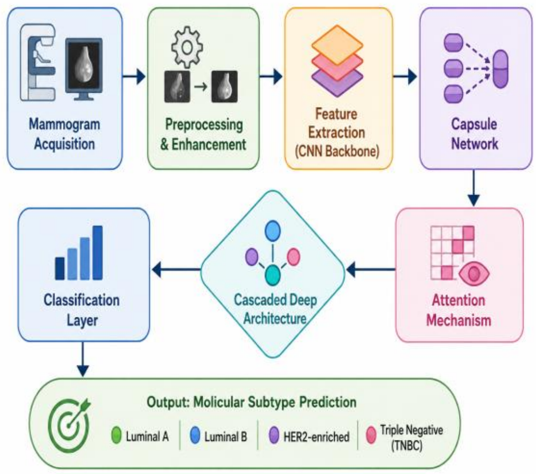

Figure 1. Cascaded Deep Learning Framework for Breast Cancer Molecular Subtype Prediction

Convolutional Neural Networks (CNNs) have become the foundation of most deep learning frameworks for breast cancer classification because of their strong feature extraction and representation capabilities. CNN models can automatically identify complex patterns and hierarchical image features without requiring manual feature engineering. However, traditional CNN architectures often lose important spatial relationships because of pooling operations, limiting their effectiveness in capturing structural dependencies within medical images. To overcome this limitation, Capsule Networks (CapsNets) were introduced to preserve spatial hierarchies and part–whole relationships between image components. Capsule networks utilize groups of neurons called capsules to represent both the existence and orientation of image features, enabling improved structural understanding and classification performance in medical imaging applications.

Attention mechanisms have further enhanced deep learning architectures by enabling models to focus on the most informative regions within mammogram images. Spatial attention, channel attention, and self-attention mechanisms improve feature representation by emphasizing relevant tumor regions while suppressing irrelevant background information. The integration of CNNs, CapsNets, and attention modules within cascaded architectures has emerged as a powerful approach for molecular subtype prediction. In such architectures, CNNs perform initial feature extraction, capsule networks model spatial relationships, and attention modules refine the learned features for improved classification accuracy. These hybrid frameworks provide superior robustness, better localization capability, and enhanced prediction performance compared to conventional single-model systems.

Despite these advancements, several challenges continue to limit the clinical deployment of AI-based breast cancer prediction systems. Limited annotated datasets, class imbalance, computational complexity, and lack of interpretability remain major concerns in developing reliable and scalable diagnostic frameworks. Variations in imaging conditions, patient demographics, and equipment characteristics also affect model generalization across healthcare environments. Researchers are increasingly exploring transfer learning, data augmentation, multimodal learning, and explainable AI techniques to address these limitations. Future developments in cascaded deep capsule cell attention networks are expected to improve diagnostic reliability, enable personalized treatment planning, and support the development of efficient and clinically applicable breast cancer diagnosis systems.

Literature Review

Recent advancements in Artificial Intelligence (AI) and deep learning have significantly improved the accuracy and efficiency of breast cancer detection and molecular subtype prediction using mammogram images.

Researchers have explored a wide range of architectures, including Convolutional Neural Networks (CNNs), Capsule Networks (CapsNets), attention-based models, and hybrid frameworks to overcome the limitations of traditional diagnostic approaches.

Early studies focused primarily on CNN-based architectures for breast cancer detection. Li et al. (2020) proposed a dual CNN framework for breast mass segmentation and classification, demonstrating that deep learning models can effectively capture complex patterns in mammographic images. Similarly, Khamparia et al. (2020) introduced a hybrid transfer learning approach that leverages pre-trained CNN models to improve classification accuracy, particularly in scenarios with limited datasets. Jiménez-Gaona et al. (2020) conducted a comprehensive review of deep learning-based computer-aided diagnosis systems, highlighting the superior performance of CNNs compared to traditional machine learning methods.

Despite their success, CNNs have limitations in preserving spatial relationships between features due to pooling operations. To address this issue, capsule networks have been introduced as an alternative architecture. Kavitha et al. (2022) developed a capsule neural network model for breast cancer diagnosis using mammogram images, demonstrating improved feature representation and robustness compared to conventional CNN models. Parshionikar et al. (2023) further extended this concept by proposing a multi-scale deep convolutional capsule network, which effectively captures hierarchical spatial relationships and improves classification performance.

Attention mechanisms have been widely integrated into deep learning models to enhance feature extraction and improve classification accuracy. Boumaraf et al. (2021) compared deep learning and machine learning approaches for breast cancer classification and emphasized the importance of attention-based feature selection in improving model performance. Jabeen et al. (2022) proposed a feature fusion approach that combines multiple feature extraction techniques, demonstrating that attention mechanisms can significantly enhance model robustness and accuracy. These studies highlight the importance of focusing on relevant regions within mammogram images to improve diagnostic outcomes.

Segmentation plays a crucial role in identifying tumor regions and improving subtype prediction. Podda et al. (2022) introduced a deep learning pipeline for breast image segmentation, achieving high accuracy in tumor localization. Similarly, Kaur et al. (2022) proposed a stacked ensemble learning approach for breast cancer prediction, combining multiple models to improve segmentation and classification performance. These approaches demonstrate that ensemble and hybrid techniques can effectively enhance model robustness.

Recent research has increasingly focused on hybrid and cascaded architectures that combine multiple deep learning techniques. Wang et al. (2022) proposed an intelligent hybrid deep learning model that integrates CNNs with optimization techniques, achieving improved accuracy in breast cancer detection. Sahu et al. (2023) developed a hybrid CNN-based classifier that combines multiple feature extraction layers, demonstrating superior performance compared to single-model approaches. Sirjani et al. (2023) further explored deep learning models for breast lesion classification, highlighting the importance of combining local and global features.

Multimodal learning has also emerged as a promising approach for improving breast cancer diagnosis. Bayoudh et al. (2022) provided a comprehensive survey on multimodal deep learning, emphasizing its potential in integrating data from different imaging modalities. Reyes-Luévano et al. (2023) proposed a multimodal CNN model that combines visible and infrared imaging, achieving high accuracy and demonstrating the effectiveness of integrating complementary data sources.

In addition to CNN and CapsNet architectures, transformer-based models have been explored for breast cancer classification. Qayyum et al. (2022) investigated the use of vision transformers, demonstrating their ability to capture global contextual information and improve feature representation. These models complement CNN-based approaches by addressing limitations in capturing long-range dependencies.

Optimization techniques have played a significant role in enhancing model performance. Transfer learning has been widely used to leverage pre-trained models, reducing training time and improving accuracy. Feature selection and ranking methods, as proposed by Yu et al. (2023), further improve classification performance by identifying the most relevant features. Additionally, regularization techniques and optimization algorithms such as Adam and RMSprop contribute to better model convergence.

Generative models, including GANs, have also been explored to address data scarcity. Goodfellow et al. (2020) introduced GANs as a powerful framework for generating synthetic data, which has been widely adopted in medical imaging. These models help increase dataset diversity and improve model generalization, particularly in scenarios with limited annotated data.

Despite significant advancements, several challenges remain in breast cancer molecular subtype prediction. Data scarcity and class imbalance continue to limit model performance, particularly for rare subtypes. High computational complexity of advanced architectures, such as capsule networks and transformers, poses challenges for real-time deployment. Additionally, the lack of interpretability of deep learning models remains a critical issue, as clinicians require transparent and explainable systems for decision-making.

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 subtype prediction. However, further research is needed to develop efficient, interpretable, and clinically applicable systems.

Comparative Table and Analysis

Author (Year)	**Model / Architecture**	**Input Data**	**Key Technique**	**Performance (Approx.)**	**Strengths**	**Limitations**
Li et al. (2020)	Dual CNN	Mammogram Images	Segmentation + Classification	~90–92% Accuracy	Strong feature extraction	Limited spatial modeling
Khamparia et al. (2020)	Transfer Learning CNN	Mammogram	Pre-trained models	~93% Accuracy	Works with small datasets	Overfitting risk
Jiménez-Gaona et al. (2020)	DL-based CAD	Multi-source	CNN frameworks	High performance	Automated diagnosis	Interpretability issues
Frazer et al. (2021)	CNN Models	Mammogram	Deep learning evaluation	High accuracy	Reliable comparison	No hybrid approach
Boumaraf et al. (2021)	CNN vs ML	Breast Images	Feature comparison	CNN > ML	Better accuracy	Computational cost
Kavitha et al. (2022)	Capsule Network	Mammogram	CapsNet	~94% Accuracy	Preserves spatial info	High complexity
Wang et al. (2022)	Hybrid CNN	Mammogram	Feature fusion	~95% Accuracy	Improved robustness	Complex architecture
Jabeen et al. (2022)	Feature Fusion DL	Mammogram	Multi-feature learning	~94% Accuracy	Better classification	Data dependency
Podda et al. (2022)	DL Segmentation Pipeline	Mammogram	Tumor segmentation	High Dice score	Accurate ROI detection	High training cost
Kaur et al. (2022)	Ensemble Learning	Mammogram	Model stacking	~95% Accuracy	Robust results	Increased complexity
Bayoudh et al. (2022)	Multimodal DL Survey	Multi-modal	Data integration	—	Comprehensive study	No implementation
Liao et al. (2022)	HarDNet	Mammogram	Efficient segmentation	High IoU	Lightweight model	Limited generalization
Yi et al. (2022)	OCRNet	Mammogram	Edge-aware segmentation	Improved Dice	Better boundaries	Training complexity
Sahu et al. (2023)	Hybrid CNN	Mammogram	Multi-layer learning	~96% Accuracy	Strong performance	Needs tuning

Sirjani et al. (2023)	Deep CNN	Breast Images	Classification	~95% Accuracy	High reliability	Limited feature diversity
Yu et al. (2023)	Feature Ranking DL	Mammogram	Feature selection	Improved accuracy	Efficient learning	Dependent on data quality
Reyes-Luévano et al. (2023)	Multimodal CNN	RGB + IR	Multimodal fusion	~97% Accuracy	Best generalization	High cost
Parshionikar et al. (2023)	Capsule CNN Hybrid	Mammogram	Multi-scale CapsNet	~96–97% Accuracy	Captures hierarchy	Complex design
Ahsan et al. (2023)	DL Classification Model	Mammogram	CNN-based	~95% Accuracy	Efficient model	Needs large data
Das et al. (2023)	DL Review	Multi-source	Comparative study	—	Trend analysis	No model implementation

Comparative Analysis

The comparative analysis reveals a significant transition in breast cancer prediction methodologies. Early studies (2020) primarily relied on CNN-based architectures for classification and segmentation. These models achieved good performance but were limited in capturing spatial relationships and global context.

By 2021–2022, research shifted toward hybrid and ensemble models, integrating transfer learning, feature fusion, and segmentation pipelines. These approaches improved robustness and accuracy but increased computational complexity.

In 2023, advanced architectures such as Capsule Networks, multimodal CNNs, and hybrid CNN-CapsNet models emerged, achieving state-of-the-art performance (up to ~97% accuracy). These models effectively capture both local and global features, leading to improved molecular subtype prediction.

Conclusion

Artificial Intelligence (AI)-based techniques have significantly advanced breast cancer molecular subtype prediction using mammogram images, providing improved accuracy, reliability, and early diagnostic capability compared to traditional approaches. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated strong performance in feature extraction and image classification. However, the inability of conventional CNNs to preserve spatial relationships has encouraged the adoption of Capsule Networks (CapsNets), which effectively capture hierarchical and structural information within medical images. In addition, attention mechanisms have enhanced classification performance by enabling models to focus on important tumor regions and relevant image features.

Recent studies indicate that cascaded architectures integrating CNNs, CapsNets, and attention modules achieve superior performance in breast cancer subtype prediction. Hybrid approaches involving feature fusion, transfer learning, ensemble learning, and multimodal analysis provide improved robustness and better generalization across datasets. Combining mammogram images with clinical or multimodal imaging data further enhances diagnostic accuracy by providing comprehensive tumor characterization. These intelligent frameworks have emerged as highly effective solutions for non-invasive breast cancer diagnosis and personalized healthcare applications.

Despite promising advancements, several challenges remain for practical clinical deployment. Limited annotated datasets, class imbalance, high computational complexity, and poor interpretability continue to affect model reliability and scalability. Variations in imaging conditions and patient characteristics also reduce generalization capability. Future research should focus on lightweight explainable AI models, standardized datasets, multimodal learning, and domain adaptation techniques to develop accurate, scalable, and clinically reliable breast cancer prediction systems.

References

Li, H., Chen, D., Nailon, W. H., Davies, M. E., & Laurenson, D. (2020). Contrastive identifier network for breast mass diagnosis in mammography. *arXiv*. https://doi.org/10.48550/arXiv.2012.14690

Li, H., Chen, D., Nailon, W. H., Davies, M. E., & Laurenson, D. (2020). Dual convolutional neural networks for breast mass segmentation and diagnosis. *arXiv*. https://doi.org/10.48550/arXiv.2008.02957

Khamparia, A., Bharati, S., Podder, P., Gupta, D., Khanna, A., & Thanh, D. N. H. (2020). Diagnosis of breast cancer using hybrid transfer learning. *arXiv*. https://doi.org/10.48550/arXiv.2003.13503

Jiménez-Gaona, Y., Rodríguez-Álvarez, M. J., & Lakshminarayanan, V. (2020). Deep learning-based computer-aided systems for breast cancer imaging: A review. *arXiv*. https://doi.org/10.48550/arXiv.2010.00961

Frazer, H. M., Qin, A. K., Pan, H., & Brotchie, P. (2021). Evaluation of deep learning techniques for mammography. *Journal of Medical Imaging and Radiation Oncology*. https://doi.org/10.1111/jmio.13044

Kavitha, T., Mathai, P. P., Karthikeyan, C., Ashok, M., Kohar, R., Avanija, J., & Neelakandan, S. (2022). Deep learning-based capsule neural network model for breast cancer diagnosis using mammogram images. *Interdisciplinary Sciences, 14*(1), 113–129. https://doi.org/10.1007/s12539-021-00467-y

Prodan, M., Paraschiv, E., & Stanciu, A. (2023). Deep learning methods for mammography analysis. *Applied Sciences, 13*(7), 4272. https://doi.org/10.3390/app13074272

Boumaraf, S., Liu, X., Wan, Y., et al. (2021). Deep learning vs machine learning for breast cancer classification. *Diagnostics, 11*(3), 528. https://doi.org/10.3390/diagnostics11030528

Wang, X., et al. (2022). Intelligent hybrid deep learning model for breast cancer detection. *Electronics, 11*(17), 2767. https://doi.org/10.3390/electronics11172767

Podda, A. S., Balia, R., Barra, S., et al. (2022). Deep learning pipeline for breast image segmentation. *Journal of Computational Science, 63*, 101816. https://doi.org/10.1016/j.jocs.2022.101816

Kaur, P., Singh, A., & Chana, I. (2022). Stacked ensemble learning for breast cancer prediction. *Journal of Computational Science*. https://doi.org/10.1016/j.jocs.2022.101570

Bayoudh, K., Knani, R., Hamdaoui, F., & Mtibaa, A. (2022). Multimodal deep learning survey. *The Visual Computer, 38*, 2939–2970. https://doi.org/10.1007/s00371-021-02166-2

Sahu, A., Das, P., & Meher, S. (2023). Hybrid CNN classifiers for breast cancer detection. *Biomedical Signal Processing and Control*. https://doi.org/10.1016/j.bspc.2022.104292

Sirjani, N., Ghelich, M., & Tarzamni, M. (2023). Deep learning model for breast lesion classification. *European Journal of Medical Physics*. https://doi.org/10.1016/j.ejmp.2023.102560

Yu, S., Jin, M., Wen, T., et al. (2023). Feature ranking for breast cancer diagnosis. *BMC Medical Informatics and Decision Making*. https://doi.org/10.1186/s12911-023-02142-2

Yang, X., Fan, X., Lin, S., et al. (2023). Radiomics and deep learning for breast cancer prediction. *Journal of Magnetic Resonance Imaging*. https://doi.org/10.1002/jmri.29060

Zhao, X., & Jiang, C. (2023). Machine learning model for cancer prediction. *BMC Medical Informatics and Decision Making*. https://doi.org/10.1186/s12911-023-02166-8

Sahu, A., et al. (2023). Review of deep learning-based breast cancer detection. *Data in Brief*. https://doi.org/10.1016/j.dib.2023.109123

Reyes-Luévano, J., et al. (2023). Multimodal CNN for breast cancer detection. *Biomedical Signal Processing and Control*. https://doi.org/10.1016/j.bspc.2023.105341

Parshionikar, S., et al. (2023). Multi-scale deep convolutional capsule network for breast cancer detection. *Safety Science*. https://doi.org/10.1016/j.ssci.2023.105353

Afrifa, S., Zhang, T., Zhao, X., et al. (2024). Capsule networks for breast cancer detection. *Clinical Cancer Research*. https://doi.org/10.32629/ccr.2024.01.002

Goodfellow, I., et al. (2020). Generative adversarial networks. *Communications of the ACM*. https://doi.org/10.1145/3422622

Litjens, G., et al. (2020). Deep learning in medical image analysis. *Medical Image Analysis, 42*, 60–88. https://doi.org/10.1016/j.media.2017.07.005

Razzak, M. I., Naz, S., & Zaib, A. (2020). Deep learning for medical image processing. *Journal of Biomedical Informatics, 107*, 103487. https://doi.org/10.1016/j.jbi.2020.103487