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Breast Cancer Histopathology Feature Selection and Classification Using Deep Learning Models: A Review

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A B S T R A C T

Breast cancer remains a significant public health concern worldwide, with early detection and accurate classification playing crucial roles in improving patient outcomes. Histopathology, the gold standard for breast cancer diagnosis, involves the microscopic examination of tissue samples. With the advent of deep learning models, particularly convolutional neural networks (CNNs), there has been a paradigm shift in the automated analysis of histopathological images, offering potential advancements in accuracy and efficiency. This review paper comprehensively explores the landscape of breast cancer histopathology feature selection and classification using deep learning models. Beginning with an overview of breast cancer histopathology and the challenges associated with traditional diagnostic methods, the review highlights the potential of deep learning techniques in revolutionizing histopathological image analysis. Through an analysis of the literature, this review identifies trends, advancements, and best practices in feature selection and classification using deep learning models for breast cancer histopathology. It discusses the effectiveness of different architectures, optimization techniques, and data augmentation strategies employed in the literature. Furthermore, the review critically evaluates the strengths and weaknesses of existing approaches, highlighting areas for future research and development

Keywords: Deep learning, Convolutional Neural Network, Histopathology Images, Breast Cancer, Classification, Feature Selection

1. Introduction

H Cancer, a pervasive global health concern, stands as one of the foremost contributors to human mortality worldwide. Particularly impactful among women, breast cancer-related deaths surpass those associated with other types of cancers, resulting in a substantial toll each year (Siegel et al., 2017). The development of breast cancer originates from alterations in breast tissue, often discernible through the identification of palpable lumps and observable changes from normal conditions. Screening procedures, encompassing mammography, breast ultrasound, biopsy, and various other methods, play a critical role in the early detection and diagnosis of this debilitating disease. Notably, the biopsy, a procedure involving the extraction of tissue for microscopic examination, remains the sole diagnostic method capable of definitively confirming the cancerous nature of suspicious areas.

Breast cancer, a prevalent invasive malignancy among women, stands as the second leading cause of cancer-related mortality, surpassed only by lung cancer (Chun, 2018). This alarming statistic underscores the profound impact of breast cancer on global health. The International Agency for Research on Cancer (IARC), an integral entity within the World Health Organization (WHO) (2018), reveals that in the year 2012 alone, cancer-related deaths worldwide amounted to a staggering 8.2 million. This distressing figure attests to the formidable challenges posed by cancer on a global scale. Projections by Boyle and Levin (2008) indicate a concerning trajectory, with the anticipated surge in new cancer cases reaching over 27 million by the year 2030. This anticipated escalation serves as a clarion call for heightened research efforts, innovative diagnostic methodologies, and effective intervention strategies to curb the escalating burden of breast cancer. The profound implications of these statistics not only necessitate a comprehensive understanding of the disease but also underscore the imperative for advancements in diagnostic and therapeutic approaches.

Breast cancer diagnosis relies on both histology and radiology images. While radiology images can pinpoint areas of abnormality, they cannot definitively determine if these areas are cancerous. Biopsy, on the other hand, involves examining tissue extracted from the body to ascertain the presence, cause, or extent of diseases like cancer. It remains the most reliable method for confirming cancer. Following biopsy, histopathologists assess the tissue to identify cancerous regions and assess malignancy. However, inaccuracies can arise if histopathologists lack adequate training, leading to incorrect diagnoses. A shortage of specialists may result in extended tissue sample storage periods. Even among expert histopathologists, discrepancies in diagnosis can occur. Despite advancements in diagnostic imaging, the final grading and staging of breast cancer still rely on pathologists visually inspecting histological samples under microscopes (Wakili et al., 2022).

The diagnosis of breast cancer involves a multifaceted approach, encompassing medical imaging techniques such as histology and radiology images. Radiology images play a pivotal role in identifying areas of abnormality, providing crucial spatial information (He et al., 2018). However, it is essential to note that radiological analysis alone cannot definitively ascertain whether the identified area is cancerous, as emphasized by He et al. (2018).

To establish a conclusive diagnosis, the gold standard remains the biopsy, a meticulous process where tissue samples are extracted and scrutinized under a microscope to determine the presence of cancer (National Breast Cancer Foundation, 2018). This method offers a definitive means of identifying the malignancy of an area. Subsequent to the biopsy, the diagnostic process relies heavily on the expertise of histopathologists, who, according to He et al. (2018), meticulously examine the tissue for the presence of abnormal or cancerous cells. The significance of this histopathological examination is underscored by Bardou et al. (2018), who highlight the ability of histology images to distinguish between cell nucleus types and their architectural patterns. Through visual examination, histopathologists discern regularities in cell shapes and tissue distributions, ultimately determining cancerous regions and the degree of malignancy.

The intricate nature of histopathological analysis underscores the critical importance of well-trained histopathologists in ensuring accurate diagnoses. The potential for misdiagnosis exists if histopathologists lack sufficient training and expertise, emphasizing the need for continuous professional development and rigorous training programs to uphold diagnostic accuracy (Bardou et al., 2018).

While technological advancements have led to improved survival rates, there has been a concurrent rise in the incidence of breast cancer cases. Among these cases, invasive ductal carcinoma (IDC) constitutes approximately 80%. Various methods, including physical examination, mammography, ultrasound, breast MRI, and biopsy, are employed by medical professionals to detect IDC. Biopsy, particularly, involves the microscopic examination of suspicious tissue observed on mammograms, a process demanding considerable time, expertise, and precision from pathologists. Consequently, the development of computer-aided systems has emerged as a significant area of focus to streamline and enhance the efficiency of pathological examinations (Seemendra et al., 2021).

With the evolution of machine learning and image processing techniques, considerable research efforts have been directed towards the creation of more effective and efficient models for breast cancer detection. Machine learning, a branch of computer science, leverages data and past experiences to predict outcomes for unseen data. Numerous methodologies have been explored and applied in the quest to develop robust machine learning models tailored for breast cancer detection (Seemendra et al., 2021).

Despite fast medical improvements, histopathological image analysis remains the most often utilized technique for diagnosing BC. Breast cancer is classified as a histopathological image based on its diverse tumor morphological characteristics (Salim & Sarath, 2023).

Deep learning, a subfield of artificial intelligence within the realm of machine learning, represents a significant advancement over traditional machine learning techniques such as neural networks, Support Vector Machines (SVM), and Extreme Learning Machines (ELM). Unlike its predecessors, which struggle with the direct processing of raw data, deep learning technology possesses the capability to automatically discern feature representations and classification methods essential for accurate detection and classification through computational means. This capability substantially enhances the efficacy of machine learning processes (Ragab et al., 2019).

At its core, deep learning functions as a feature learning methodology, facilitating the transformation of raw data into higher-level and more abstract representations via simple nonlinear models. By employing a cascade of transformations, deep learning enables the acquisition of highly complex functions. Its architecture typically comprises a multi-layer stack of basic modules, primarily dedicated to learning, alongside mappings for nonlinear input-output computations. Each module within this stack operates to augment the selectivity and invariance of the expression of its input.

A prominent example of a deep learning model is the Convolutional Neural Network (CNN), characterized by a sequence of modules. Initial modules typically consist of a convolution layer and a pooling layer, serving to detect local connections within upper-layer features and amalgamate similar features in semantics, respectively. The distinctive aspect of deep learning lies in the fact that the features of each layer are not explicitly designed but rather learned from the data through a standard learning process. CNN, as a pivotal structure within deep learning, exemplifies this characteristic (Al-Jabbar et al., 2023).

Our primary contribution in this paper is the synthesis and analysis of existing literature on the application of deep learning algorithms in breast cancer histopathology feature selection and optimization. By evaluating the strengths and limitations of various approaches, this review aims to offer insights into the current state-of-the-art techniques and highlight potential areas for future research.

The remainder of the paper includes the following sections: Section 2 presents the Research Methodology; Related Work is presented in Section 3; Section 4 presents the Discussion of the paper; and the Conclusion and Acknowledgments are presented in Sections 5 and 6 respectively.

2. Research Methodology

The methodology used in this review aims to systematically investigate the role of deep learning models in breast cancer histopathology feature selection and classification. The approach encompasses defining research questions and objectives, conducting thorough literature searches, selecting significant papers, and critically analyzing their contributions.

2.1 Research Questions

I. What are the available research works in the literature on deep learning models for breast cancer histopathology feature selection and classification?

II. How effective are these deep learning models in improving the accuracy and efficiency of histopathology image analysis?

These research questions focus on assessing the effectiveness of deep learning models in the context of breast cancer histopathology. Our objective is to compare various deep learning techniques, elucidate their strengths and limitations, and identify best practices for their integration into breast cancer diagnostic frameworks.

3. Related Work

In the field of computational medical imaging, the utilization of deep convolutional neural networks (CNN) has demonstrated considerable success, as evidenced by studies such as Zhang et al. (2016). These CNNs are adept at hierarchically and unsupervised learning imaging features from raw data, progressively deciphering the intricacies of increasingly complex datasets directly from their raw images. This approach allows for the identification of relevant characteristics without the need for predetermined feature extraction by the user. The integration of variable selection is seamlessly achieved during both the learning of characteristics from raw data and the acquired features, as observed in the work of Das et al. (2023). Furthermore, this integrated approach extends to supervised classification, wherein the same architecture accommodates the optimization and automation of the entire process, as illustrated by the studies conducted by Adeniyi and Adeshina (2021). Comparative analyses between conventional multi-step computational imaging methods and deep learning techniques have consistently favored the latter, particularly in the context of screening mammograms for breast cancer. Notably, studies such as Dhomane and Swati Shinde (2023) have demonstrated superior classification accuracy and mortality prediction associated with deep learning methodologies.

Analyzing breast cancer poses considerable challenges and often leads to disagreements among experts. However, the integration of computer-aided diagnosis (CAD) systems can enhance diagnostic accuracy and reduce processing time through interdisciplinary approaches. CAD systems assist healthcare professionals in interpreting medical images by detecting and identifying potential abnormalities within the images. The adoption of CAD for automatic classification of histopathological images not only enhances diagnostic efficiency at a low cost but also yields more objective and accurate diagnosis results. Consequently, there is a growing demand for CAD systems (Wakili et al., 2022).

Despite these advancements, existing breast cancer diagnosis models face challenges related to complexity, cost, dependence on human expertise, and inaccuracies. Moreover, the availability of datasets poses a practical challenge in this field of research. Furthermore, every deep learning model requires evaluation metrics to assess its performance. Performance evaluation metrics are essential components of deep learning models as they serve as indicators of progress.

A dataset comprising 7,909 breast cancer (BC) histopathology images obtained from 82 patients was introduced (Spanhol et al., 2015). The dataset is currently accessible to the public through http://web.inf.ufpr.br/vri/breast-cancer-database. The dataset encompasses both benign and malignant images, and the primary objective associated with it is the automated classification of these images into two classes, presenting a potentially valuable computer-aided diagnosis tool for clinicians. To gauge the complexity of this classification task, the authors presented preliminary results achieved with state-of-the-art image classification systems, demonstrating accuracy levels ranging from 80% to 85% and indicating room for improvement. By offering this dataset along with a standardized evaluation protocol to the scientific community, the authors aspired to catalyze collaboration among researchers in both medical and machine learning domains to propel advancements in this clinical application.

3.1 Deep Learning Algorithms

Spanhol et al. (2016) illustrated the feasibility of leveraging an existing CNN architecture, specifically AlexNet, originally designed for classifying color images of objects, for the classification of breast cancer histopathological images. Several strategies for training the CNN architecture were proposed, involving the extraction of patches obtained randomly or through a sliding window mechanism. These strategies were devised to accommodate the high-resolution nature of these textured images without necessitating alterations to the CNN architecture initially designed for low-resolution images. Additionally, the authors explored the combination of different CNNs using simple fusion rules, resulting in modest enhancements in recognition rates. The achieved accuracies were reported as 90.0%, 88.4%, 84.6%, and 86.1% for magnification factors of 40x, 100x, 200x, and 400x, respectively.

A groundbreaking convolutional neural network (CNN) was meticulously crafted, comprising a convolutional layer, a small SE-ResNet module, and a fully connected layer (Jiang et al., 2019). Notably, the innovation introduced by the authors included a small SE ResNet module, representing an advancement in the fusion of a residual module and Squeeze-and-Excitation block. Remarkably, this new module exhibited comparable performance with a reduced number of parameters, showcasing efficiency in model design. They proposed a novel learning rate scheduler designed to achieve excellent performance without the need for intricate fine-tuning of the learning rate. The application of their model extended to the automatic classification of breast cancer histology images, specifically utilizing the BreakHis dataset, for categorization into benign and malignant classes, as well as eight subtypes. The reported results indicated the model's remarkable performance, achieving an accuracy of 98.87% for binary classification and demonstrating accuracies ranging between 90.66% and 93.81% for multi-class classification.

A comprehensive investigation utilized pre-trained Convolutional Neural Network (CNN) models, specifically DenseNet-161 and ResNet-50, employing a transfer learning technique (Talo, 2019),. The primary objective was to classify digital histopathology patches into their corresponding whole slide images. This study encompassed the testing of the proposed pre-trained models on both grayscale and color histopathology images, allowing for a comparative evaluation of their classification performance. The results revealed that the proposed DenseNet-161 model, when tested on grayscale images, achieved an outstanding classification accuracy of 97.89%, surpassing existing state-of-the-art methods. Furthermore, the ResNet-50 pre-trained model, when tested on color images from the Kimia Path24 dataset, demonstrated exceptional performance with a classification accuracy of 98.87%. Notably, the proposed pre-trained models consistently outperformed existing state-of-the-art methods across all performance metrics, establishing their efficacy in accurately classifying digital pathology patches into 24 categories.

In a study conducted by Kassani et al. (2019), a sophisticated ensemble deep learning approach was introduced for the automatic binary classification of breast histology images. The proposed ensemble model intricately integrated three pre-trained Convolutional Neural Networks (CNNs) - VGG19, MobileNet, and DenseNet. This ensemble model played a crucial role in the feature representation and extraction phases. Subsequently, the extracted features underwent processing through a multi-layer perceptron classifier to facilitate the binary classification task. To enhance the robustness of the model, various preprocessing and CNN tuning techniques were meticulously applied. These included stain-normalization, data augmentation, hyperparameter tuning, and fine-tuning. The efficacy of the proposed method was rigorously evaluated across four publicly available benchmark datasets: ICIAR, BreakHis, PatchCamelyon, and Bioimaging.The proposed multi-model ensemble method obtained better predictions than single classifiers and machine learning algorithms with accuracies of 98.13%, 95.00%, 94.64% and 83.10% for BreakHis, ICIAR, PatchCamelyon and Bioimaging datasets, respectively.

The focus of Adeshina et al. (2018) was on addressing the challenging issue of intra-class classification of Breast Histopathology images, specifically into eight classes distinguishing between Benign and Malignant Cell categories. The existing manual process of features extraction and classification was identified as prone to inaccuracies, resulting in a high rate of false negatives and associated mortality. To mitigate these challenges, the researchers leveraged the effectiveness of Deep Convolutional Neural Networks (DCNN) for image classification. They adopted a DCNN architecture and employed an Ensemble learning method, utilizing the TensorFlow Framework with Backpropagation training and Rectified Linear Unit (ReLU) activation function. This approach aimed to achieve precise and automated classification of Breast Histopathology images.They achieved inter-class classification accuracy of 91.5% with the BreakHis dataset.

Xie et al. (2019) Introduce the application of deep learning in the analysis of histopathological images related to breast cancer through both supervised and unsupervised deep convolutional neural networks (CNNs). Initially, the authors employ transfer learning techniques to adapt the Inception_V3 and Inception_ResNet_V2 architectures for binary and multi-class issues in the classification of breast cancer histopathological images. In addressing the challenge posed by imbalanced subclasses, the authors normalize the subclasses using Ductal Carcinoma as the baseline. This normalization involves various transformations such as flipping images vertically and horizontally and rotating them counterclockwise by 90 and 180 degrees. The experimental results of the supervised classification of breast cancer histopathological images, along with comparisons to outcomes from other studies, highlight the superior performance of the Inception_V3 and Inception_ResNet_V2 architectures in breast cancer diagnosis. Notably, the findings underscore Inception_ResNet_V2 as the most effective deep learning architecture for analyzing histopathological images in breast cancer diagnosis. Subsequently, the authors utilize Inception_ResNet_V2 to extract features for unsupervised analysis, employing a novel autoencoder network to transform these features into a low-dimensional space for clustering analysis. The outcomes of the experiments indicate that the proposed autoencoder network enhances clustering results compared to relying solely on features extracted by Inception_ResNet_V2. Collectively, the experimental results suggest that Inception_ResNet_V2-based deep transfer learning introduces a novel approach for analyzing histopathological images in breast cancer, offering potential advancements in diagnostic methodologies.

A pioneering strategy for discriminating Invasive Ductal Carcinoma (IDC) cells in histopathology slides was introduced. The authors suggested a model derived from the Inception architecture, incorporating a novel multi-level batch normalization module positioned between each convolutional step (Romero et al., 2019). This module served as a fundamental block for feature extraction within a Convolutional Neural Network (CNN) architecture. The researchers utilized the open IDC dataset, achieving a balanced accuracy of 0.89 and an F1 score of 0.90. These results surpassed the performance of recent state-of-the-art classification algorithms tested on the same public dataset.

A novel deep feature fusion approach was introduced, leveraging the 'residual connection' concept from ResNet to effectively extract distinctive features (Minh et al., 2019). This method aimed to enhance the classification performance of Breast cancer prediction on histopathology images. Specifically, the authors fused features extracted from various blocks of InceptionV3, considering the concatenated features as rich information capable of capturing deep image features. The study conducted three experiments to explore factors affecting classification performance: 1) Feature extractor or Finetuning? 2) Normalization vs. Non-normalization, and 3) The effectiveness of their deep feature fusion method. The dataset comprised 400 microscopy images from the ICIAR 2018 Grand Challenge on Breast Cancer histopathology images, categorized into four classes representing different aggressiveness levels of breast cancer (Normal, Benign, In Situ Carcinoma, Invasive Carcinoma).Experimental results showed that their proposed deep feature fusion method can achieve a very high classification accuracy with 95% in distinguishing 4 types of cancer classes and 97.5% for differentiating two combined groups of cancer, which are Carcinoma (N+B) and Non carcinoma (IS+IV).

A Convolutional Neural Network (CNN) was employed to classify and identify breast cancer images sourced from the public BreakHis dataset (Nguyen et al., 2019). The dataset comprises 7,909 histopathology images of breast cancer with four benign subclasses and four malignant subclasses. The primary objective of this research was to automate the multi-classification of breast cancer images into eight classes, aiming to contribute to the reduction of death rates and the preservation of lives globally. The proposed method involved resizing the original images to construct the CNN model for classifying different breast cancer classes. The accuracy achieved by the constructed model was deemed acceptable at 73.68%, considering the specific characteristics of the input images.

In research conducted by Wakili et al. (2022), their contribution unfolds in two significant dimensions. Firstly, they embarked on a concise exploration into deep-learning-based models tailored for the classification of histopathological images. This survey aimed to scrutinize prevalent training-testing ratios, seeking to discern the most favored and optimized configurations. Their investigation revealed that while the prevailing training-testing ratio for histopathological image classification stands at 70%:30%, the best of performance, particularly in terms of accuracy, is attained with a training-testing ratio of 80%:20% on a consistent dataset. Secondly, they introduced a novel methodology named DenTnet, specifically designed for the classification of breast cancer histopathological images. DenTnet innovatively leverages the principles of transfer learning to address the challenge of feature extraction from identical distributions. The proposed DenTnet methodology exhibits notable superiority compared to several prominent deep learning approaches, showcasing remarkable detection accuracy, with results peaking at 99.28% on the BreaKHis dataset under the training-testing ratio of 80%:20%. This achievement was coupled with commendable generalization abilities and expedited computational speeds, thereby mitigating the limitations inherent in existing methodologies, such as high computational demands and the constraint of identical feature distributions.

Seemendra et al. (2021) employed histological images for the detection and classification of invasive ductal carcinoma. Convolutional neural networks (CNNs) were utilized as a sophisticated and effective technique for image analysis in machine learning. A comparative analysis of various renowned deep learning models was conducted, employing pre-trained CNN architectures with fine-tuning to develop an efficient solution. They applied image augmentation techniques to enhance the efficacy of the solution. The investigated models include VGG, ResNet, DenseNet, MobileNet, and EfficientNet. The most optimal outcome was achieved through fine-tuning the VGG19 architecture in combination with appropriate image augmentation. This approach results in a sensitivity of 93.05% and a precision of 94.46%. The F-Score was enhanced by 10.2% compared to previous research. An accuracy of 86.97% was attained using a pre-trained DenseNet model, surpassing the accuracy achieved in recent studies, which reached 85.41%.

After a comprehensive evaluation of various state-of-the-art deep learning techniques and algorithms in medical data processing, Yari and Nguyen (2020) present a novel deep transfer learning-based model. Leveraging pre-trained DCNN models trained on the extensive ImageNet dataset, the proposed model enhances existing systems in both binary and multi-class classification tasks. Initially, the weights of the pre-trained DenseNet121 model on ImageNet were utilized as initial weights, followed by fine-tuning with a deep classifier and data augmentation to discern between malignant and benign samples in binary and multi-class classification scenarios. In multi-class classification, the proposed model achieved image-level accuracy of up to 97%, while in binary classification, it achieved image-level accuracy of up to 100%. These results surpassed the accuracies reported in prior studies across multiple performance metrics in breast cancer CAD systems. The proposed method exhibits flexibility and scalability, enabling easy expansion to cover the detection of other diseases in the future and integration with additional CNNs to enhance its generalization capabilities.

Adeniyi and Adeshina (2021) investigated the effectiveness of a discriminative fine-tuning algorithm applied to ResNet and DenseNet Models, which optimized a range of hyperparameters and employed a cyclical learning rate policy per iteration during training. Their proposed method undergoes testing on the Public BreakHis Dataset with magnifications of 100X and 400X. Experimental results, evaluated based on the Accuracy metric, demonstrated promising outcomes. Densenet achieved an accuracy of 95.33% at 100X magnification and 94.34% at 400X magnification, while Resnet achieved 96.56% at 100X magnification and 96.3% at 400X magnification. These results underscored the efficacy of the optimization approach for classifying breast cancer histopathology images in clinical settings.

Dhomane and Shinde (2023) noted that in contemporary medical image analysis, the demand for high accuracy in proposed algorithms is paramount. Their study endeavors to evaluate and compare the efficacy of different deep learning algorithms previously employed in the classification of breast cancer (BC) histopathological images. The research seeked to determine the most effective binary classification models for databases containing histopathology images of breast cancer.The study explored the implementation and performance evaluation of EfficientNetV2 models, an advanced deep learning architecture, in the binary classification of breast cancer histopathological images. Various deep learning algorithms were contrasted to ascertain their comparative performance. The paper also discussed potential avenues for future research in this domain.

In a study, conventional image processing techniques were utilized for cancer-type detection (Kutluer et al., 2023). While more recent research has shifted towards employing advanced deep learning methods, particularly recurrent neural networks and convolutional neural networks (CNNs). This paper explored the application of popular deep learning architectures such as ResNet-50, GoogLeNet, InceptionV3, and MobileNetV2, integrating a novel feature selection approach to classify cancer types using both a local binary class dataset and the multi-class BACH dataset. The classification performance of the deep learning methods augmented with the proposed feature selection technique got promising results, achieving an accuracy of 98.89% for the local binary class dataset and 92.17% for the BACH dataset. These results surpassed many existing findings in the literature. The findings suggested that the proposed methodology exhibits high accuracy and efficiency in detecting and classifying cancerous tissue types across both datasets.

Sangeetha et al. (2023) explained that transfer learning has emerged as a potent technique for precise classification of medical images, particularly in the realm of deep learning models. This method is primarily employed to facilitate model training on limited datasets by leveraging knowledge acquired from related tasks and transferring it to a new task. Its application has shown promising results in enhancing the accuracy of classification models, especially in the domain of breast cancer classification from medical images. Compared to conventional training approaches, transfer learning models exhibit superior accuracy in cancer classification. Moreover, they offer advantages such as increased computational efficiency, mitigation of overfitting, and the ability to generate meaningful representations from datasets with limited annotations. Given the challenges associated with obtaining large annotated medical image datasets, transfer learning proved particularly advantageous in medical imaging tasks. This paper delved into the utilization of transfer learning for precise breast cancer classification in medical imaging and explores its potential contributions to disease diagnosis.

In research, the authors stated, convolutional Neural Network (CNN) models represent a pivotal deep learning architecture aimed at accurately classifying breast cancer. Their paper served a dual purpose (Shahidi et al., 2020). Firstly, it focuses on the exploration of various deep learning models for classifying breast cancer histopathology images. The study discerns the most precise models concerning binary, four, and eight classifications within breast cancer histopathology image databases. Disparate accuracy scores across the deep learning models on identical databases underscore the influence of additional factors like pre-processing, data augmentation, and transfer learning techniques on model accuracy. Secondly, the manuscript endeavors to scrutinize the latest models with limited or no examination in prior studies. Models such as ResNeXt, Dual Path Net, SENet, and NASNet, noted for their cutting-edge results on the ImageNet database, are assessed for binary and eight classifications on the BreakHis dataset, along with the BACH dataset for four classifications. These models are juxtaposed against earlier studies to identify and advocate the most advanced models for each classification task. Notably, given that the Inception-ResNet-V2 architecture yields the optimal results for binary and eight classifications, it is comprehensively evaluated in this study to furnish a robust comparative analysis. In summary, this paper furnishes a thorough evaluation and discourse on the experimental setups across various studies conducted on breast cancer histopathology images.

After evaluating deep learning techniques and algorithms for processing breast histological data, efforts were made to enhance the accuracy of existing systems (Yari et al., 2020). Their study introduced two efficient deep transfer learning-based models that leverage pre-trained DCNNs trained on a large collection of images from the ImageNet dataset. These models aimed to surpass current state-of-the-art systems in both binary and multiclass classification tasks. Their approach involved transferring pre-trained weights from ResNet50 and DenseNet121 models trained on ImageNet as initial weights. These are then fine-tuned with a deep classifier using data augmentation to identify various malignant and benign tissue samples in binary and multiclass settings. Their proposed models underwent rigorous evaluation with optimized hyperparameters, considering magnification-dependent and magnification-independent classification modes. In multiclass classification, their proposed system achieved an accuracy of up to 98%, while in binary classification, it achieved up to 100% accuracy. These results surpassed the accuracies reported in previous studies across all defined performance metrics for breast cancer computer-aided diagnosis (CAD) systems utilizing histological images.

Arooj et al. (2022) proposed a model that addressed the classification of benign and malignant breast cancer, which is a crucial aspect of computer-aided diagnosis systems relying on histopathology and ultrasound images. Over the past few decades, there has been significant progress in automating the identification and classification of tumors, facilitating early detection and improving patient outcomes. Deep learning (DL), machine learning (ML), and transfer learning (TL) techniques have been instrumental in addressing various medical challenges. While previous literature has explored tumor categorization and identification using different models, limitations persist, often due to inadequate datasets. To address these challenges, they proposed a methodology for the automatic identification and diagnosis of breast cancer. Their primary contribution lies in the utilization of transfer learning techniques applied to three datasets: A, B, and C, with an additional dataset A2 derived from A but with two classes. Their study incorporated both ultrasound and histopathology images. They employed a customized CNN-AlexNet model trained specifically to accommodate the characteristics of the datasets, which represents another significant contribution of this work. Their findings demonstrated that the proposed system, enhanced by transfer learning, achieved superior accuracy compared to existing models across datasets A, B, C, and A2.

Kousalya and Saranya (2021) proposed for the detection and classification of breast cancer in breast cytology videos utilizing Convolutional and pooling layers for feature extraction, followed by classification using a dense layer. Both Convolutional Neural Network (CNN) and DenseNet architectures were employed to extract image features, which were then inputted into a fully connected layer for classifying malignant and benign cells. The models were trained, validated, and tested for image classification of breast cancer. Their comparative analysis was conducted to assess the performance of the proposed CNN and DenseNet models. The suggested system demonstrated superior accuracy in diagnosing and classifying breast tumors from histological images compared to CNN and DenseNet models. Hyperparameter tuning was utilized to evaluate the efficiency of CNN and DenseNet.

Srikantamurthy et al. (2023) proposed a hybrid model for classifying benign and malignant breast cancer subtypes, a combination of convolutional neural network (CNN) and long short-term memory recurrent neural network (LSTM RNN) was developed. This hybrid CNN-LSTM model, utilizing transfer learning from ImageNet, was designed to classify and predict four subtypes of each cancer category. Evaluation of the proposed model was conducted on the BreakHis dataset, comprising 2480 benign and 5429 malignant cancer images captured at magnifications of 40×, 100×, 200×, and 400×. Their performance of the hybrid CNN-LSTM model was compared with existing CNN models commonly used for breast histopathological image classification, including VGG-16, ResNet50, and Inception models. Each model was trained using three different optimizers—adaptive moment estimator (Adam), root mean square propagation (RMSProp), and stochastic gradient descent (SGD)—with varying numbers of epochs. Results indicated that the Adam optimizer achieved the highest accuracy and lowest model loss for both the training and validation sets across all models. Their proposed hybrid CNN-LSTM model demonstrated the highest overall accuracy of 99% for binary classification of benign and malignant cancer, and 92.5% for multi-class classification of benign and malignant cancer subtypes. In conclusion, the transfer learning approach employed in their study outperformed existing machine and deep learning models in classifying benign and malignant cancer subtypes. Additionally, the proposed method exhibits feasibility for classifying other types of cancers and diseases.

Vulli et al. (2022) stated that the current study presented a pioneering technique for automated diagnosis and detection of metastases from whole slide images, leveraging the FastAI framework and the 1-cycle policy. They conducted a comparative analysis with existing methodologies. Their proposed model exhibited superior performance, achieving over 97.4% accuracy, surpassing previous state-of-the-art methods. A mobile application was developed to facilitate prompt response, enabling the collection of user data and models for diagnosing early-stage metastases. These findings suggested that the proposed model could aid general practitioners in accurately assessing breast cancer cases, thereby mitigating potential complications and mortality rates. Through advancements in digital image processing, there has been a significant enhancement in histopathologic interpretation and diagnostic precision.

Zheng et al. (2023) introduced a novel deep ensemble model designed for binary classification of breast histopathological images depicting benign and malignant lesions. The BreaKHis dataset was partitioned randomly into training, validation, and test subsets. Data augmentation techniques were employed to equalize the representation of benign and malignant samples. The selection of VGG16, Xception, ResNet50, and DenseNet201 as base classifiers was based on their performance in transfer learning tasks and their complementarity in network architecture. The ensemble network model, prioritizing accuracy as the criterion, achieved a remarkable accuracy of 98.90% in image-level binary classification. To evaluate the efficacy of their approach, they conducted experimental comparisons with the latest transformer and multilayer perceptron (MLP) models using the same dataset. Their ensemble model demonstrated a notable advantage of 5%–20%, underscoring its extensive capabilities in classification tasks. This research focused on enhancing the performance of classification models through an ensemble algorithm. Transfer learning played a pivotal role in improving the classification accuracy and training efficiency, particularly for small datasets. Their model exhibited potential to surpass many existing approaches in terms of accuracy and holds promise for applications in auxiliary medical diagnosis.

Zhong et al. (2020) introduced a model for classifying metastatic cancer images based on the DenseNet Block architecture. The model was designed to accurately identify metastatic cancer in small image patches extracted from larger digital pathology scans. Their proposed approach was evaluated using a modified version of the PatchCamelyon (PCam) benchmark dataset, which simplified the clinically-relevant task of metastasis detection into a binary image classification problem. Experimental results demonstrated that their model surpassed the performance of classical methods such as ResNet34 and VGG19. Additionally, they conducted experiments on data augmentation and investigated the relationship between the number of batches processed and the loss value during the training and validation phases.

Joseph et al. (2022), handcrafted feature extraction techniques such as Hu moment, Haralick textures, and color histogram, alongside Deep Neural Network (DNN), were applied to multi-classify breast cancer using histopathological images sourced from the BreakHis dataset. These handcrafted features were utilized to train DNN classifiers, consisting of four dense layers and Softmax activation. Data augmentation was implemented to mitigate overfitting concerns. Results demonstrated that employing handcrafted feature extraction alongside DNN classifiers yielded superior performance in breast cancer multi-classification compared to existing methodologies. Furthermore, it was observed that data augmentation significantly contributed to enhancing classification accuracy. The proposed method achieved notable accuracy scores of 97.87% for 40x, 97.60% for 100x, 96.10% for 200x, and 96.84% for 400x magnification-dependent histopathological image classification. These findings underscore the efficacy of utilizing handcrafted feature extraction methods in conjunction with DNN classifiers for multi-classifying breast cancer using histopathological images, surpassing the performance of many existing approaches in the field.

Sharma and Mehra (2020) thoroughly investigated and compared two distinct machine learning methodologies for automatically classifying breast cancer on a balanced BreakHis dataset, considering magnification dependence. The first method involved extracting handcrafted features using Hu moment, color histogram, and Haralick textures. These features were then employed to train traditional classifiers. The second method adopted transfer learning, utilizing pre-existing networks (VGG16, VGG19, and ResNet50) as both feature extractors and baseline models. Results indicated that employing pre-trained networks as feature extractors gave superior performance compared to the baseline and handcrafted approaches across all magnifications. Furthermore, data augmentation significantly enhanced classification accuracy. Utilizing the VGG16 network with linear SVM achieved the highest accuracy, evaluated in patch-based accuracies (93.97% for 40×, 92.92% for 100×, 91.23% for 200×, and 91.79% for 400×) and patient-based accuracies (93.25% for 40×, 91.87% for 100×, 91.5% for 200×, and 92.31% for 400×) for magnification-dependent histopathological image classification. Moreover "Fibro-adenoma" (benign) and "Mucous Carcinoma" (malignant) classes were identified as the most challenging classes across all magnification factors.

In their study, Öztürka and Akdemir (2019) introduced the HIC-net, a convolutional neural network (CNN) model designed for the automated identification of cancerous regions within whole-slide histopathological images (WSI). Their architecture of the HIC-net facilitated window-based classification by segmenting the WSI into distinct planes. An efficient pre-processing step was incorporated into their methodology to enhance the predictability of image components and improve the training processes. The evaluation of the HIC-net algorithm utilizes a sizable dataset comprising 30,656 images, of which 23,040 were allocated for training, 2,560 for validation, and 5,056 for testing purposes. Their HIC-net exhibited superior performance compared to other contemporary CNN algorithms, boasting an impressive AUC score of 97.7%. When assessing the classification outcomes of HIC-net using the softmax function, their model demonstrated a sensitivity of 96.71%, specificity of 95.7%, and accuracy of 96.21%, surpassing the efficacy of existing techniques commonly employed in cancer research endeavors.

Elmannai et al. (2021) concentrated on analyzing breast cancer histopathological images obtained through microscopic scans of breast tissue samples. Their approach involved combining two deep convolutional neural networks (DCNNs) to extract distinctive image features using transfer learning. They utilized pre-trained Inception and Xception models simultaneously. The extracted feature maps were merged and subjected to dropout regularization before being inputted into the final fully connected layers for classification. They adopted a hierarchical classification strategy, starting with sub-image classification followed by whole-image classification based on majority voting and maximum probability rules. The classification framework encompassed four tissue malignancy levels: normal, benign, in situ carcinoma, and invasive carcinoma. Experimentation was conducted on the Breast Cancer Histology (BACH) dataset. The sub-image classification achieved an overall accuracy of 97.29%, with a sensitivity of 99.58% for carcinoma cases. For whole-image classification, the overall accuracy reached 100% through majority voting and 95% through maximum probability fusion decision. Numerical results demonstrated that their proposed method surpassed previous approaches in terms of accuracy and sensitivity. Furthermore, the proposed design exhibits scalability for extending classification to whole-slide histology images.

Li et al. (2019) noted that classification of breast cancer histology images, spanning normal, benign, and malignant subclasses, hinges on factors such as cell density, variability, organization, and overall tissue morphology. To capture these features comprehensively, they extracted patches of varying sizes from histology images, encompassing both cell-level and tissue-level characteristics. However, some cell-level patches may lack sufficient information to align with the image tag. To address this, they proposed a patch screening method that combines clustering algorithms with CNNs to identify more discriminative patches. Their approach was applied to the 4-class classification of breast cancer histology images, achieving 95% accuracy on the initial test set and 88.89% accuracy on the overall test set. These results were competitive with those obtained from other state-of-the-art methodologies.

Yan et al. (2019) introduced a novel hybrid convolutional and recurrent deep neural network designed specifically for breast cancer histopathological image classification. By leveraging the comprehensive multilevel feature representation inherent in histopathological image patches, their approach combines the strengths of convolutional and recurrent neural networks while preserving both short-term and long-term spatial correlations among patches. The experimental findings demonstrated the superiority of their method over existing approaches, achieving an average accuracy of 91.3% for the 4-class classification task. They contributed to the research community by providing a dataset comprising 3771 breast cancer histopathological images, now publicly accessible at http://ear.ict.ac.cn/?page_id=1616. This dataset stands out as the largest publicly available resource for breast cancer histopathological image classification, covering a diverse range of subclasses across various age groups. As a result, it offers ample data diversity to address challenges related to the relatively low classification accuracy of benign images.

In many computer-aided diagnosis (CAD) systems, conventional methods have been utilized for feature extraction, which are prone to inaccuracies in diagnosis and are time-intensive.

In a study, both CAD diagnostics and computations aim to alleviate the workload of pathologists while enhancing diagnostic precision (Senan et al., 2020). Their study introduced a convolutional neural network (CNN), specifically AlexNet, to extract profound features from the BreaKHis dataset for the classification of breast cancer as either benign or malignant. The study conducted four experiments corresponding to different magnification factors (40X, 100X, 200X, and 400X), each comprising 1407 images. Training and validation of the network were performed on 80% of the tissue images, with the remaining 20% used for testing. Their proposed system achieved an accuracy, sensitivity, specificity, and AUC of 95%, 97%, 90%, and 99.36%, respectively.

Hameed et al. (2020) proposed an ensemble deep learning method for accurately classifying non-carcinoma and carcinoma breast cancer histopathology images using a dataset they compiled. They trained four distinct models based on pre-existing VGG16 and VGG19 architectures. Initially, they conducted 5-fold cross-validation on each individual model, including fully-trained VGG16, fine-tuned VGG16, fully-trained VGG19, and fine-tuned VGG19 models. Subsequently, they implemented an ensemble approach by aggregating predicted probabilities. Their findings indicated that the ensemble of fine-tuned VGG16 and VGG19 models exhibited competitive classification performance, particularly for the carcinoma class. This ensemble achieved a sensitivity of 97.73% for carcinoma classification and an overall accuracy of 95.29%, accompanied by an F1 score of 95.29%. The experimental outcomes underscore the effectiveness of their proposed deep learning methodology for automatically classifying complex histopathology images of breast cancer, particularly those depicting carcinoma.

3.2 Deep Learning Optimized with Evolutionary Algorithms

Salim and Sarath (2023) explored the challenge of automatic segmentation of breast tumors persists due to the inherent difficulties posed by poor contrast and unclear structures of tumor cells in histopathological images. To overcome these obstacles, an innovative approach for breast cancer (BC) detection and classification was proposed, leveraging a DenseNet-based Chronological Circle Inspired Optimization Algorithm (CCIOA). Their proposed methodology integrates Deep Learning (DL) techniques to achieve precise segmentation and identification of BC lesions. Specifically, ResuNet++ was used for image segmentation, while an efficient optimization method known as Invasive Water Ebola Optimization (IWEO) was utilized to fine-tune the parameters of the DL network. DenseNet was used for BC detection, with CCIOA serving as the optimization algorithm for training the DenseNet model. The performance of the CCIOA-DenseNet model was evaluated using key metrics such as accuracy, True Positive Rate (TPR), and True Negative Rate (TNR). Experimental results demonstrate the superior performance of the CCIOA-DenseNet model, achieving an accuracy of 97.1%, TPR of 96.6%, and TNR of 95.4%.

Atban et al. (2023) revolved around the selection of optimal features essential for the classification of breast cancer pathological images while mitigating the challenges posed by the curse of dimensionality. To address this, the study leveraged optimized deep features as a solution. The approach entailed employing the ResNet18 architecture to extract deep features crucial for the classification task. Subsequently, meta-heuristic algorithms such as Particle Swarm Optimization (PSO), Atom Search Optimization (ASO), and Equilibrium Optimizer (EO) are harnessed to further refine and enhance the representativeness of these features in breast cancer pathological images. The significance of optimized deep features in classification is comprehensively investigated by employing traditional machine learning (ML) algorithms. The experimental evaluation of the proposed approach was conducted using the publicly available benchmark dataset BreakHis. The experimental outcomes underscore the efficacy of the proposed methodology, particularly highlighting the notable performance achieved when utilizing features derived from ResNet18-EO. Specifically, the proposed approach attains an impressive F-score of 97.75% when employing the Support Vector Machine (SVM) with gaussian and radial-based functions (RBF) on these optimized features.

Das et al. (2023) stated that contemporary approaches predominantly leverage deep learning models for predictive tasks. These methods may encounter challenges related to high-dimensional features and the inclusion of irrelevant or redundant information. To address this limitation, their study adopted the widely used particle swarm optimization (PSO) algorithm to attain an optimal feature set. Initial preprocessing involved obtaining stain-normalized images, followed by feature extraction using a pre-trained MobileNet model. Evaluation was conducted on a recent dataset provided by the ICIAR BACH 2018 grand challenge. Experimental findings demonstrated a notable 6.25% enhancement in recognition accuracy while reducing features by approximately 54%. Furthermore, a comparison with two state-of-the-art CNN models, InceptionResNet and DenseNet, revealed the superiority of MobileNet. The performance of their model was found to be on par with certain state-of-the-art methods applied to the BACH dataset.

3.3 Deep Learning and Machine Learning-Based Algorithms

A novel methodology for the classification of breast cancer utilizing deep learning and segmentation techniques is introduced (Ragab et al., 2019). The authors propose a new Computer-Aided Detection (CAD) system designed for the classification of benign and malignant mass tumors in breast mammography images. Two segmentation approaches are employed in this CAD system. The first method involves manual determination of the Region of Interest (ROI), while the second approach utilizes threshold and region-based techniques. For feature extraction, a Deep Convolutional Neural Network (DCNN) is employed, with the well-known AlexNet architecture fine-tuned to classify two classes instead of the conventional 1,000 classes. The last fully connected (fc) layer is connected to a Support Vector Machine (SVM) classifier to enhance accuracy. The experiments utilize publicly available datasets, namely the Digital Database for Screening Mammography (DDSM) and the Curated Breast Imaging Subset of DDSM (CBIS-DDSM). Data augmentation is applied to increase the input data size through the generation of new data using rotation. The accuracy of the newly trained DCNN architecture is reported as 71.01% when manually cropping the ROI from the mammogram. The highest Area Under the Curve (AUC) achieved is 0.88 (88%) for samples obtained from both segmentation techniques. Furthermore, when using samples from CBIS-DDSM, the accuracy of the DCNN increases to 73.6%. Consequently, the SVM accuracy reaches 87.2%, with an AUC of 0.94 (94%), representing the highest AUC value compared to prior studies under similar conditions.

Abbasniya et al. (2022) delve into the examination of sixteen distinct pre-trained networks, with a particular emphasis on their classification capabilities, a section that has received inadequate attention in the community. The Convolutional Neural Networks (CNNs) scrutinized, Inception-ResNet-v2 model, integrating both residual and inception networks, exhibits unparalleled efficacy in extracting features from breast cancer histopathology images. They ensembled the classification phase with Categorical Boosting (CatBoost), Extreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM), which provided the highest average accuracy. To evaluate the proposed methodology, denoted as IRv2-CXL, the Breast Cancer Histopathological Image Classification (BreakHis) dataset served as the benchmark. Their Experimental findings underscored the superior performance of IRv2-CXL when compared to existing state-of-the-art methodologies.

In a research, three methodologies, each comprising three systems, were devised to facilitate the diagnosis of both multi-class and binary breast cancer datasets, enabling the discrimination between benign and malignant types across different magnification factors, specifically 40× and 400× (Al-Jabbar et al., 2023). Their initial approach for diagnosing breast cancer datasets involved the utilization of an artificial neural network (ANN) incorporating selected features extracted from VGG-19 and ResNet-18 architectures. The second methodology employed an ANN model with combined features derived from VGG-19 and ResNet-18, both pre and post principal component analysis (PCA). The third technique involved employing an ANN model with hybrid features, which consisted of a fusion between features extracted from VGG-19 or ResNet-18 and handcrafted features obtained through various methods including Fuzzy Color Histogram (FCH), Local Binary Pattern (LBP), Discrete Wavelet Transform (DWT), and Gray Level Co-occurrence Matrix (GLCM). In the context of multi-class datasets, the ANN model leveraging hybrid features from VGG-19 and handcrafted features achieved notable precision (95.86%), accuracy (97.3%), sensitivity (96.75%), Area Under Curve (AUC) (99.37%), and specificity (99.81%) when operating on images at a magnification factor of 400×. Similarly, when dealing with binary class datasets, the ANN model employing hybrid features from VGG-19 and handcrafted features demonstrated impressive precision (99.74%), accuracy (99.7%), sensitivity (100%), AUC (99.85%), and specificity (100%) at the same magnification factor of 400×.

Zerouaoui and Idri (2022) implemented and assessed twenty-eight hybrid architectures by combining seven contemporary deep learning techniques for feature extraction, namely DenseNet201, Inception V3, Inception ResNet V2, MobileNet V2, ResNet 50, VGG16, and VGG19, along with four classifiers comprising MLP, SVM, DT, and KNN. Their primary objective was to perform a binary classification of breast pathological images from the BreakHis and FNAC datasets. The efficacy of the developed architectures was gauged through multiple evaluation methods, including four classification performance metrics (accuracy, precision, recall, and F1-score), the Scott Knott (SK) statistical test for clustering the proposed architectures, and the Borda Count voting method for ranking the top-performing architectures. Their findings underscored the potential of integrating deep learning techniques for feature extraction with classical classifiers to differentiate between malignant and benign tumors in breast cancer classification tasks. The hybrid architecture incorporating the MLP classifier and DenseNet 201 for feature extraction (referred to as MDEN) emerged as the most effective configuration, exhibiting significantly higher accuracy rates. MDEN achieved an accuracy of 99% over the FNAC dataset and impressive accuracy values of 92.61%, 92%, 93.93%, and 91.73% across different magnification factors (40X, 100X, 200X, and 400X) of the BreakHis dataset.

Nathan et al. (2019) conducted a comparative analysis of two transfer learning methodologies: Deep Feature Classification and Fine-tuning Convolutional Neural Networks (ConvNets) for the diagnosis of Breast Cancer malignancy. The benchmarking of results was performed utilizing the BreaKHis dataset in conjunction with pretrained models including ResNet-50, InceptionV2, and DenseNet-169. Deep feature classification resulted an accuracy ranging from 81% to 95% when employed in combination with Logistic Regression, LightGBM, and Random Forest classifiers. The accuracy of the Fine-tuned DenseNet-169 model surpasses that of all other classification models, achieving a performance level of 99.25 ± 0.4%.

Nakach et al. (2023) introduced a methodology utilizing transfer learning and ensemble learning techniques for the binary classification of breast cancer histological images across various magnification factors in the BreakHis dataset, including 40×, 100×, 200×, and 400×. The proposed approach employed bagging ensembles constructed with a hybrid architecture, combining pretrained deep learning models for feature extraction with machine learning classifiers such as MLP, SVM, and KNN as base learners. The investigation compared and evaluated several aspects, including different configurations of bagging ensembles with varying numbers of base learners (3, 5, 7, and 9), individual classifiers against the best-performing bagging ensembles, and the top-performing bagging ensembles for each feature extractor and magnification factor. The selection of the most effective models iwas determined through statistical analysis using the Scott Knott (SK) test, with further ranking conducted using the Borda Count voting system. The optimal bagging ensemble, achieving a mean accuracy of 93.98%, comprises 3 base learners, utilizes 200× magnification, employed MLP as the classifier, and employed DenseNet201 as the feature extractor. These findings underscore the effectiveness and promise of bagging hybrid deep learning methodologies for automating the classification of histopathological breast cancer images.

Yadavendra and Chand (2020) explored diverse machine learning techniques, including logistic regression, random forest, support vector classifier (SVC), AdaBoost classifier, bagging classifier, voting classifier, and Xception model, for breast cancer tumor classification, evaluating their respective performances. Utilizing a standard dataset comprising over two hundred thousand color patches extracted from breast histopathology images, each patch sized at 50 × 50 and scanned at 40× resolution, the dataset was splited into 60% for training, 20% for validation, and 20% for testing across all classifiers. The logistic regression classifier had a precision, recall, and F1 measure scores of 0.72, while the random forest method achieved scores of 0.80 for each metric. Both bagging and voting classifiers demonstrated values of 0.81 for precision, recall, and F1 scores. Meanwhile, SVC and AdaBoost classifiers attained scores of 0.82 across all three metrics. In contrast, employing the Xception model, a deep learning method, resulted in precision, recall, and F1 measure scores of 0.90 under the same conditions. Consequently, the Xception method exhibits superior performance across all performance measures for breast cancer tumor classification. Their research underscored the significance of achieving more accurate tumor classification in less time, potentially enhancing awareness of breast cancer and alleviating concerns surrounding tumors.

A novel patch-based approach named Pa-DBN-BC was introduced for the detection and classification of breast cancer in histopathology images, employing Deep Belief Network (DBN) (Hirra et al., 2020). Feature extraction was conducted through a combination of unsupervised pre-training and supervised fine-tuning phases. The network autonomously extracts features from image patches, and logistic regression was employed to classify these patches within histopathology images. Extracted patch features were inputted into the model, which then presents results as a probability matrix, indicating either a positive sample (cancer) or a negative sample (background). Training and testing of the proposed model were performed on a dataset comprising whole-slide histopathology images from four distinct cohorts, achieving an accuracy rate of 86%. The proposed methodology exhibits superiority over traditional approaches by automatically learning optimal features, as demonstrated through experimental results surpassing previously proposed deep learning methods.

Sheikh et al. (2020) introduced the Multi-Scale Input and Multi-Feature Network (MSI-MFNet) model, which integrates multi-resolution hierarchical feature maps within its dense connectivity structure to comprehend the structural and textural characteristics of tissues across different scales. The MSI-MFNet assesses disease probability at both patch and image levels. Performance evaluation conducted on two publicly available benchmark datasets indicates superior results compared to existing models. Ablation studies underscore the significance of incorporating multi-scale input and multi-feature maps in enhancing model performance, with their proposed approach demonstrating improved accuracy, sensitivity, and specificity over state-of-the-art counterparts.

Abedhaliem et al. (2022) introduced an automated classification system that combined pre-trained deep Convolutional Neural Networks (CNNs) for feature extraction with multilevel hand-crafted features. The pre-trained models utilized include ResNet18, Inception ResNet v2, ShuffleNet, and Xception. Hand-crafted features such as Haralick textures, Rotation and Scale-invariant Hybrid image Descriptor (RSHD), Local Diagonal Extrema Pattern (LDEP), Speeded up robust features (SURF), Colored Histogram, and the Dense Invariant Feature Transform (DSIFT) set were extracted. These features undergo dimensionality reduction using Principal Component Analysis (PCA) and were then used as feature vectors for training three classifiers: Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbor (KNN). Their proposed methodology was assessed for efficacy using the ICIAR-2018 dataset, which comprises histopathology images of four classes: invasive carcinoma, in-situ carcinoma, benign tumors, and normal tissue. Their experimental findings demonstrated an accuracy of 96.97% for the proposed method.

4. Discussion

In this work, we analyzed research on the application deep learning algorithms for breast cancer histopathology feature selection and classification. We have focused on the use cases of deep learning models in the classification of breast cancer images. As the research landscape evolves, the integration of CNNs into breast cancer histology image analysis not only represents a technological leap but also signifies a promising avenue for refining the intricacies of diagnostic methodologies. The depth and adaptability of CNNs stand poised to contribute significantly to the ongoing efforts aimed at enhancing the precision and efficiency of breast cancer diagnosis (Sangeetha, et al., 2023). In addition, we discovered that evolutionary algorithms play a crucial role in deep feature selection and parameter adjustment in deep learning algorithms. They are highly suited for the feature selection step due to their wide search and optimization abilities. Hence in our research, we have explored various models and techniques for the classification and feature selection of breast cancer.

Error! Reference source not found. presents a comparative analysis of different deep learning techniques, methodology, contributions, and experimental limitations. The discussion further elaborates on the emerging trends, open research questions, and potential future directions in the field of breast cancer classification and feature selection using deep learning techniques.

Table 1 - Comparative Analyses of Different Deep Learning Techniques.

S/N	Source	Problem	Technique	Methodology	Contribution	Limitation
1	(Spanhol et al., 2016)	Breast cancer histopathological image classification	Improving classification accuracy for high-resolution histopathological images	Utilization of deep learning approach, extraction of image patches, adaptation of AlexNet architecture	Achieved accuracies of 90.0%, 88.4%, 84.6%, and 86.1% for magnification factors of 40x, 100x, 200x, and 400x, respectively	Minimizing complexity and computational costs, Handling high-resolution textures
2	(Jiang et al., 2019)	Breast cancer histopathological image classification	Enhancing classification accuracy using a novel CNN design	Implementation of a novel CNN architecture, introduction of small SE ResNet module, and innovative learning rate scheduler	Achieved an accuracy of 98.87% for binary classification and accuracies between 90.66% and 93.81% for multi-class classification	Parameter efficiency, Learning rate optimization, Automated image classification
3	(Talo 2019)	Digital histopathology patch classification	Achieving accurate classification using pre-trained CNN models	Utilization of DenseNet-161 and ResNet-50 pre-trained models, Transfer learning technique, Evaluation on grayscale and color histopathology images	DenseNet-161 achieved 97.89% accuracy on grayscale images; ResNet-50 achieved 98.87% accuracy on color images, Outperformed state-of-the-art methods	Comparative analysis of classification performance, Transferability to different image types
4	(Kassani et al., 2019)	Automatic binary classification of breast histology images	Enhancing accuracy through an ensemble deep learning approach	Integration of VGG19, MobileNet, and DenseNet CNNs, Feature extraction via ensemble model, Utilization of preprocessing and tuning techniques	Achieved accuracies of 98.13%, 95.00%, 94.64%, and 83.10% for BreakHis, ICIAR, PatchCamelyon, and Bioimaging datasets, respectively	Robustness, Model generalization, Comparative evaluation of ensemble vs. single classifiers
5	(Adeshina et al., 2018)	Intra-class classification of Breast Histopathology images	Achieving accurate automated classification of images into eight classes	Adoption of DCNN architecture, Ensemble learning with TensorFlow, Backpropagation training, ReLU activation function	Inter-class classification accuracy of 91.5% with the BreakHis dataset	Inaccuracies in manual classification, High false negative rates, Mortality risk
6	(Xie et al., 2019)	Analysis of breast cancer histopathological images using deep learning	Introducing deep learning for supervised and unsupervised analysis of histopathological	- Adaptation of Inception_V3 and Inception_ResNet_V2 architectures via transfer learning	Superiority of Inception_V3 and Inception_ResNet_V2 in histopathological	Influence of imbalanced subclass images. Optimal deep learning architecture for

			breast cancer images	- Subclass balancing by transforming images - Utilization of Inception_ResNet_V 2 for feature extraction - Introduction of a new autoencoder network for unsupervised analysis by transforming features from Inception_ResNet_V 2	image classification. Inception_ResNet_ V2 as the best architecture for breast cancer diagnosis. Improved clustering with proposed autoencoder network for unsupervised analysis Deep transfer learning as a novel approach for histopathological image analysis of breast cancer	breast cancer diagnosis. Effective unsupervised analysis via autoencoder network
7	(Ragab et al., 2019)	Breast cancer classification using deep learning and segmentation	Introducing a novel methodology for breast cancer classification through deep learning and segmentation techniques	They used Deep Convolutional Neural Network (DCNN), AlexNet and Support Vector Machine(SVM).	The accuracy of the new-trained DCNN architecture is 73.06%.	Manual ROI cropping limitation. Previous works using similar conditions lacked optimal AUC values
8	Romero et al. (2019)	Discrimination of IDC cells in histopathology slides	Introduce a novel strategy for IDC cell discrimination	Utilize a model derived from Inception architecture, introduce a multi-level batch normalization module, incorporate it into CNN architecture for feature extraction	Achieved balanced accuracy of 0.89 and F1 score of 0.90, outperforming recent state-of-the-art classification algorithms on IDC dataset	Lack of efficient methods for IDC cell discrimination in histopathology
9	(Minh et al., 2019)	Breast cancer classification on histopathology images	Introduce a deep feature fusion method using residual connection	Fuse features from different InceptionV3 blocks for enhanced classification performance, conduct experiments on key factors influencing performance	Achieved 95% accuracy in distinguishing 4 types of cancer classes, and 97.5% for differentiating combined groups (Carcinoma vs. Non-carcinoma)	Lack of effective methods for breast cancer classification on histopathology images
10	(Nguyen et al., 2019)	Multi-classification of breast cancer images	Utilize CNN for automated classification of breast cancer images from BreakHis dataset	Construct CNN model based on resized original images for multi-class classification of breast cancer	Achieved 73.68% accuracy in multi-classification	Lack of automated methods for multi-classification of breast cancer images

11	(Spanhol et al., 2015)	The need for automated classification of breast cancer histopathology images	Develop a valuable computer-aided diagnosis tool for clinicians by classifying histopathology images into benign and malignant classes	Introduced a dataset of 7,909 BC histopathology images from 82 patients. Preliminary results with state-of-the-art image classification systems.	A publicly accessible dataset and standardized evaluation protocol to foster collaboration among medical and machine learning researchers.	Identified the potential for improvement in classification accuracy (80% to 85%).
12	(Salim and Sarath, 2023)	Poor contrast and unclear tumor cell structures pose challenges for automatic segmentation of breast tumors	DenseNet-based Chronological Circle Inspired Optimization Algorithm (CCIOA)	Integration of Deep Learning (DL) approaches for precise segmentation and identification of breast cancer lesions using ResuNet++ for segmentation and IWEO for parameter fine-tuning. DenseNet is utilized for breast cancer detection with CCIOA serving as the optimization algorithm for model training.	Improved accuracy, TPR, and TNR in breast cancer detection and classification. Achieved an accuracy of 97.1%.	Evaluation limited to metrics of accuracy, TPR, and TNR
13	(Wakili et al., 2022)	Need for an effective methodology for breast cancer histopathological image classification with improved accuracy and generalization capabilities	DenTnet (Transfer learning-based DenseNet model)	Leveraging transfer learning to extract features and enhance classification accuracy	Detection accuracy at 99.28% on the BreaKHis dataset, robust generalization abilities, and computational efficiency	Evaluation primarily focused on detection accuracy, potential need for validation across diverse datasets
14	(Abbasniya et al., 2022)	Inadequate exploration of classification capabilities in pre-trained networks for breast cancer histopathology images	Inception-ResNet-v2 model, Ensemble of CatBoost, XGBoost, and LightGBM	Utilization of Inception-ResNet-v2 for feature extraction and ensemble of boosting algorithms for classification	Enhanced classification accuracy surpassing state-of-the-art methods	Focus primarily on accuracy, potential need for assessment of other performance metrics such as sensitivity, specificity, and computational efficiency
15	(Al-Jabbar et al., 2023)	Optimization of breast cancer diagnosis through hybrid feature utilization	ANN with hybrid features from VGG-19 or ResNet-18 and handcrafted features	Fusion of deep learning and handcrafted features through integration of PCA for feature enhancement	Improved feature representation and enhanced diagnostic performance	Focus primarily on ANN-based methodologies, potential need for comparison with other machine learning techniques. Limited evaluation across diverse

						datasets and magnification factors
16	(Zerouaoui and Idri, 2022)	Exploration of hybrid architectures	Combination of MLP classifier with DenseNet 201 (MDEN)	Development of hybrid architectures	Enhanced classification accuracy. MDEN achieved an accuracy of 99%	Limited investigation into the interpretability of the model and computational complexity
17	(Atban et al., 2021)	Efficient feature selection for breast cancer classification	Optimized deep features extraction	Utilization of ResNet18 architecture and meta-heuristic algorithms	Improved feature representation.The proposed approach attains an impressive F-score of 97.75%	Limited evaluation beyond SVM classifier and BreakHis dataset
18	(Nathan et al., 2019)	Diagnosis of Breast Cancer malignancy	Transfer learning: Deep Feature Classification and Fine-tuning ConvNets	Comparative analysis of classification methodologies	Identification of optimal approach for breast cancer diagnosis. Deep feature classification resulted an accuracy ranging from 81% to 95% when employed in combination with Logistic Regression.	The outcomes are expected to be more comprehensively evaluated in the future considering DenseNet-169 fine-tuned model will be used for semantic segmentation on whole-slide histopathology images.
19	(Seemendra et al., 2021)	Detection and classification of invasive ductal carcinoma in histological images	Employing Convolutional Neural Networks (CNNs)	Comparative analysis of various deep learning models with fine-tuning and image augmentation	Improvement in sensitivity, precision, and F-Score compared to prior research. The F-Score was enhanced by 10.2% compared to previous research	Experiment with small size images from which only deep learning models can infer useful information.
20	(Das et al., 2023)	Screening breast cancer from histology images	Utilizing particle swarm optimization (PSO) algorithm for feature selection	Preprocessing images for stain normalization, extracting features using a pre-trained MobileNet model	Enhanced recognition accuracy by 6.25% with a reduction of approximately 54% in features	They have only used BPSO as a feature selector. Hence, the use of some recent feature selection techniques might help in improving the performance in the future
21	(Yari and Nguyen, 2020)	Evaluation of deep learning methods in medical data processing	Deep transfer learning-based model leveraging pre-trained DCNNs	Utilization of pre-trained DenseNet121 weights from ImageNet followed by fine-tuning with a	Improved accuracies in both binary and multi-class classification tasks, surpassing prior studies in breast cancer CAD	The model must be trained and tested with a few more datasets in order

				deep classifier and data augmentation	systems. In multi-class classification, the proposed model achieved image-level accuracy of up to 97%, while in binary classification, it achieved image-level accuracy of up to 100%	to increase the variety and diversity of the data.
22	(Adeniyi and Adeshina, 2021)	Evaluation of discriminative fine-tuned algorithm on ResNet and DenseNet Models	Application of cyclical learning rate policy and hyperparameter optimization	Testing on the Public BreakHis Dataset with magnifications of 100X and 400X	Densenet achieved an accuracy of 95.33% at 100X magnification and 94.34% at 400X magnification, while Resnet achieved 96.56% at 100X magnification and 96.3% at 400X magnification.	Limited exploration of other hyperparameter optimization techniques and potential biases in dataset selection
23	(Dhomane & Shinde, 2023)	Evaluation of deep learning algorithms for binary classification of breast cancer histopathological images	Comparison of various deep learning algorithms	Implementation and performance assessment of EfficientNetV2 models	Identification of the most effective binary classification models and exploration of advanced deep learning architecture	Working with high-resolution and high-quality breast cancer histopathology images.
24	(Kutluer et al., 2023)	Application of deep learning methods for cancer type classification	Implementation of popular deep learning architectures with novel feature selection	Classification using local binary class dataset and multi-class BACH dataset	Achieving high accuracy in cancer type classification. With an accuracy of 98.89% for the local binary class dataset and 92.17% for the BACH dataset.	Limited evaluation on datasets other than local binary class and BACH datasets
25	(Sangeetha et al., 2023)	Enhancing breast cancer classification accuracy in medical imaging	Transfer learning	Application of transfer learning in breast cancer classification	Improved accuracy and computational efficiency	Only evaluated transfer learning in other medical imaging tasks.
26	(Nakach et al., 2023)	Binary classification of breast cancer histological images	Bagging ensembles with hybrid architectures combining pretrained deep learning models and machine	Evaluation and comparison of bagging ensembles with different base learners and magnification factors	Improved classification accuracy through the integration of deep learning and ensemble learning methodologies	Sensitivity to parameter tuning and selection; potential for overfitting with complex ensemble structures; reliance on robust feature extraction techniques

			learning classifiers			
27	(Shahidi et al., 2020)	Classification of breast cancer histopathology images	Deep learning	Exploration of various deep learning models for classifying breast cancer histopathology images. Identification of the most accurate models for binary, four, and eight classifications	Identification and proposal of state-of-the-art models for each classification task. Comprehensive evaluation of experimental setups across multiple studies.	The dataset quality and size. The high cost of equipment, such as cutting-edge scanners and data storage, represents the challenges in acquiring high-resolution images
28	(Yari et al., 2020)	Enhancement of breast cancer CAD system accuracy	Deep transfer learning	Utilization of pre-trained weights from ResNet50 and DenseNet121 models fine-tuned with a deep classifier and data augmentation.	Achievement of up to 100% accuracy in binary classification and up to 98% accuracy in multiclass classification.	The proposed models worked less accurately in 400× images.
29	(Arooj et al., 2022)	Automatic identification and diagnosis of breast cancer	Transfer Learning based on CNN-Alexnet	Developed a methodology leveraging transfer learning on datasets A, B, C, and A2, with A2 being a modified version of A. Utilization of ultrasound and histopathology images.	Used transfer learning to enhance classification accuracy, particularly with a customized CNN-AlexNet model tailored to dataset characteristics. Superior performance observed across multiple datasets.	Application of fusion on the datasets for enhance the results and test more algorithms on the datasets for optimal and robust solution
30	(Kousalya & Saranya, 2021)	Detection and classification of breast cancer in breast cytology videos	Deep Learning based Architectures like CNN and DenseNet	Employment of CNN and DenseNet architectures for feature extraction and classification.	Better accuracy in diagnosing and classifying breast tumors from histological images compared to existing models. Utilization of hyperparameter tuning for optimizing model efficiency.	Application of Convolution Neural Network with Particle Swarm Optimization (PSO) method to monitor parameter importance, enabling better discovery and exploitation.
31	(Srikantamurthy et al., 2023)	Breast Cancer Subtype Classification	Hybrid CNN-LSTM Model, Transfer Learning	Implementation of hybrid CNN-LSTM model for classifying benign and malignant breast cancer subtypes. Transfer learning from ImageNet.	Achieved highest overall accuracy in binary and multi-class classification of breast cancer subtypes. Demonstrated feasibility for classifying other	Computational complexity associated with training hybrid CNN-LSTM model. Deployment challenges in real-world clinical settings.

					types of cancers and diseases.	
32	(Vulli et al., 2022)	Automated diagnosis and detection of metastases	FastAI framework	Implementation of FastAI framework and 1-cycle policy for automated diagnosis and detection of metastases from whole slide images	Surpassed state-of-the-art methods with over 97.4% accuracy; development of mobile application	Generalization to other cancer types not examined; reliance on digital image processing
33	(Zheng et al., 2023)	Binary classification of breast histopathological images	Deep Ensemble Model	Implementation of image-level labels for binary classification; selection of base classifiers (VGG16, Xception, ResNet50, DenseNet201) based on transfer learning	Achieved an accuracy of 98.90% in image-level binary classification; outperformed transformer and MLP models by 5%–20%	Relies on availability of labeled data for training; applicability to broader datasets not explored
34	(Zhong et al., 2020)	Metastatic Cancer Image Classification	DenseNet Block	Evaluation on modified version of PatchCamelyon (PCam) benchmark dataset; Experimentation with data augmentation and batch processing	Outperformed classical methods like ResNet34 and VGG19; Study of data augmentation impact and loss value during training and validation	Limited to image patch classification; Dependency on specific architecture and dataset modifications
35	(Joseph et al., 2022)	Detection and classification of breast cancer in histopathological images	Handcrafted feature extraction and Deep Neural Network (DNN)	Utilized handcrafted feature extraction techniques and DNN classifiers	Achieved improved performance in breast cancer multi-classification with notable accuracy scores of 97.87% for 40x, 97.60% for 100x, 96.10% for 200x, and 96.84% for 400x magnification-dependent	The limitation lies in the varying impact of magnification on classification accuracy, which is contingent upon the degree of complexity present in histopathological images, escalating with higher magnification levels.
36	(Yadavendra and Chand, 2020)	Classification of breast cancer	Machine Learning Methods (Logistic Regression, Random Forest, SVC, AdaBoost, Bagging, Voting, Xception)	Utilization of breast histopathology images dataset consisting of color patches at 40x resolution	Evaluation of various classifiers for breast cancer classification, highlighting superior performance of Xception	Limited to classification task; does not address other aspects such as tumor detection or feature extraction
37	(Sharma & Mehra, 2020)	Automatic magnification-dependent multi-classification for	Comparison of two machine learning approaches:	Pre-trained networks (VGG16, VGG19, ResNet50) as feature	Superior performance of transfer learning.	Reliance on pre-trained networks.

		breast cancer detection	handcrafted features vs. transfer learning	extractors and baseline models.	Significance of data augmentation. Identification of VGG16 network with linear SVM as achieving highest accuracy.	Generalization challenge. Potential biases from data augmentation.
38	(Öztürka & Akdemir, 2019)	Automatic identification of cancerous areas on whole-slide histopathological images (WSI)	Convolutional Neural Network (CNN)	Window-based classification by segmenting WSI into planes	Introduction of HIC-net architecture with efficient pre-processing step for improved predictability and faster training. Achievement of superior performance compared to state-of-the-art CNN algorithms with an AUC score of 97.7%	Limited evaluation to histopathological images, potential challenges in generalizability to diverse datasets beyond the specific domain of cancer pathology
39	(Elmannai et al., 2021)	Breast cancer histopathological image analysis	Deep Convolutional Neural Networks (DCNNs)	Transfer learning, feature extraction, hierarchical classification	Improved accuracy and sensitivity in breast cancer classification.Sub-image classification achieved an overall accuracy of 97.29%, with a sensitivity of 99.58% for carcinoma cases.	Limited to analysis of histopathological images, potential challenges in generalizing to other types of medical images or datasets
40	(Hirra et al., 2020)	Detection and classification of breast cancer on histopathology images	Patch-based deep learning method (Pa-DBN-BC)	Utilization of Deep Belief Network (DBN) for feature extraction via unsupervised pre-training and supervised fine-tuning. Classification of image patches using logistic regression.	Introduction of a novel patch-based approach for breast cancer detection and classification. Outperforms traditional methods by automatically learning optimal features, with an accuracy of 86%	Performance limited by dataset size and diversity.
41	(Sheikh et al., 2020)	Histopathological Classification of Breast Cancer Images	Introduction of the Multi-Scale Input and Multi-Feature Network (MSI-MFNet) model.	Utilization of dense connectivity structure to fuse multi-resolution hierarchical feature maps, enabling the model to grasp structural and textural	MSI-MFNet demonstrates superior performance compared to existing models, showcasing enhanced accuracy,	The study does not address potential challenges or constraints encountered during model implementation or evaluation.

				characteristics across various tissue scales.	sensitivity, and specificity.	
42	(Li et al., 2019)	Diagnosis of breast cancer histology images with hematoxylin and eosin staining	Convolutional Neural Networks (CNNs)	Extracting patches of varying sizes from histology images to capture cell-level and tissue-level features; proposing a patch screening method combining clustering algorithms with CNNs	Achieving 95% accuracy on initial test set and 88.89% accuracy on overall test set for 4-class classification of breast cancer histology images	Some cell-level patches may lack sufficient information to align with image tag; results are competitive with other state-of-the-art methodologies but may not exceed them in all cases.
43	(Abedhaliem et al., 2022)	Automated classification of histopathology images	Combination of pre-trained CNNs and hand-crafted features	Utilization of pre-trained CNNs (ResNet18, Inception ResNet v2, ShuffleNet, Xception) for feature extraction	Achieved 96.97% accuracy in classifying histopathology images from the ICIAR-2018 dataset	Potential limitations in generalization to diverse datasets and scalability to larger datasets; computational complexity may be high due to the use of multiple classifiers and feature extraction methods.
44	(Yan et al., 2019)	Breast cancer histopathological image classification	Hybrid convolutional and recurrent deep neural network	Integration of convolutional and recurrent neural networks to leverage multilevel feature representation and preserve spatial correlations between image patches	Outperforms existing methods with an average accuracy of 91.3% for 4-class classification. Dataset comprising 3771 breast cancer histopathological images released to the scientific community	Relatively low classification accuracy for benign images due to limited data diversity in existing datasets
45	(Senan et al., 2020)	Traditional CAD systems rely on imprecise, time-consuming handcrafted feature extraction methods, limiting diagnostic accuracy and efficiency.	Proposed a convolutional neural network (CNN), specifically AlexNet, to extract deep features from the BreaKHis dataset for breast cancer classification.	Four experiments conducted at different magnification factors (40X, 100X, 200X, and 400X), each comprising 1407 images. Training and validation on 80% of tissue images, with 20% for testing.	Achieved high accuracy, sensitivity, specificity, and AUC (95%, 97%, 90%, and 99.36% respectively) in classifying breast cancer as benign or malignant.	Limited discussion on potential challenges or drawbacks of the proposed CNN approach.
46	(Hameed et al., 2020)	Classification of breast cancer histopathology images	Ensemble deep learning approach	Trained four models based on pre-trained VGG16 and VGG19 architectures	Proposed ensemble strategy by averaging predicted probabilities. With a sensitivity of 97.73% for	Limited only to classification of carcinoma and non-carcinoma classes; may not address other subclasses of breast cancer

			carcinoma classification and an overall accuracy of 95.29%.	histopathology images

4.1 Emerging Trends

The field of breast cancer histopathology feature selection and classification using deep learning models is rapidly evolving and improving. Several emerging trends highlight the current advancements and the direction in which the field is heading. In this review, we have noted below some areas on concern and interests.

The use of transfer learning, where models pre-trained on large datasets (such as ImageNet) are fine-tuned on breast cancer histopathology images, is becoming increasingly popular as in the case of Wakili et al, 2022. This approach leverages the extensive feature extraction capabilities of pre-trained models, significantly reducing the need for large annotated histopathology datasets.

Also, with the rise of deep learning in medical applications, there is a growing emphasis on explainable AI. Researchers are developing models that not only provide accurate predictions but also offer insights into the decision-making process. This is crucial for gaining the trust of medical professionals and for clinical implementation. Since AI models are a black box mostly, it is really important we gain insights into the reason of their decision making in classification and feature in field of medicine.

Combining deep learning models with traditional machine learning techniques and evolutionary algorithms is another trend. These hybrid models aim to enhance the feature selection process and improve overall classification performance by leveraging the strengths of both approaches (Salim & Sarath, 2024). This approach includes things like feature selection using evolutionary algorithms (flower pollination, genetic algorithms, and particle swarm optimization) (Das et al., 2022). In some cases, the evolutionary algorithms are used for parameter tunings and training optimizations.

4.2 Open Research Questions

Despite tremendous advances, there are still some unresolved research challenges in the field of breast cancer histopathology feature selection and classification with deep learning models. One question is how can we improve the interpretability and transparency of deep learning models in histopathology because understanding the decision-making process of deep learning models is critical for clinical acceptance. Hence, developing methods that can explain model predictions in a way that is understandable to pathologists and other medical professionals is crucial.

Another important question is what are the optimal methods for annotating and curating large histopathology datasets? The lack of large, well-annotated datasets is a significant barrier to the development of robust deep-learning models (Hameed et al., 2020). Developing efficient and scalable methods for dataset annotation and curation, with large annotated datasets can ensure the generalization ability of the models.

Furthermore, how can we mitigate the effects of data variability and imbalance in histopathology images? Histopathology images can vary significantly due to differences in staining protocols, scanner settings, and other factors. For example, the Datasets BACH and BreakHis are different in their magnification and sizes. Research in developing techniques that can standardize and normalize these images to reduce variability and address data imbalance issues is an open research endeavor.

4.3 Potential Future Directions

To address present obstacles and unanswered research issues, various potential future avenues in breast cancer histopathology feature selection and classification can be investigated utilizing deep learning models. Future research should concentrate on creating models that are reliable and generalizable across a variety of datasets and clinical contexts. This can be accomplished by combining several training datasets, advanced data augmentation techniques, and domain adaption approaches. In addition, strategies for improving the interpretability of deep learning models will be critical. This can include the use of attention mechanisms, saliency maps, and other techniques that highlight the visual regions that have the greatest influence on the model's decision-making process. Finally, using unsupervised and semi-supervised learning approaches can assist in alleviating the problems associated with inadequate annotated data (Yan et al., 2019). These strategies can use unlabelled data to increase model performance and eliminate the need for big annotated datasets.

5. Conclusion

This paper presents a comprehensive review of the state-of-the-art research works in breast cancer histopathology image feature selection and classification using deep learning models. By synthesizing the existing literature and analyzing the strengths and limitations of different approaches, this review aims to provide researchers and practitioners with insights into the potential of deep learning algorithms for enhancing the efficiency and effectiveness of breast cancer diagnosis. The integration of deep learning models in breast cancer histopathology has shown significant promise, with the potential to revolutionize diagnostic practices. By continuing to address the challenges of model interpretability, data variability, and limited annotated data, and by leveraging the strengths of hybrid models with machine learning and evolutionary algorithms, researchers can further enhance the accuracy and reliability of these models. The future of breast cancer diagnosis and treatment looks promising, with deep learning and evolutionary algorithms playing a pivotal role in advancing the field and improving patient outcomes.

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