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Application of Artificial Intelligence in Digital Histopathology: Evaluating the Effectiveness of Deep Learning for Cancer Diagnosis

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ABSTRACT

Background: Digital histopathology has become a cornerstone in cancer diagnosis, enabling detailed analysis of tissue slides to identify pathological features. Traditional methods often face challenges such as inter-observer variability and prolonged processing time, highlighting the need for faster and more accurate diagnostic approaches. Artificial Intelligence (AI), particularly deep learning algorithms, has transformed this field by enabling automated analysis of high-resolution medical images. ***Methods:*** This study employed a systematic review approach to evaluate the effectiveness of deep learning methods in cancer diagnosis based on digital imaging. Literature searches were conducted across four major electronic databases, applying stringent inclusion criteria to ensure the relevance and quality of the selected studies. ***Results:*** From a total of 1,423 identified articles, 14 met the inclusion criteria. The findings indicate that the application of deep learning in cancer diagnosis yields high diagnostic accuracy, with most studies reporting accuracy rates above 85%. In several contexts, AI-based models demonstrated performance that matched or exceeded that of clinical practitioners. ***Conclusion:*** The application of AI in digital histopathology offers significant potential to enhance the accuracy, efficiency, and accessibility of cancer diagnosis. With the ability to accelerate diagnostic workflows and support clinical decision-making, the integration of this technology could improve clinical outcomes for cancer patients globally.

Keywords: digital histopathology; cancer; artificial intelligence; deep learning; cancer diagnosis.

INTRODUCTION

Digital histopathology has become a cornerstone in cancer diagnosis, enabling detailed analysis of tissue slides to identify pathological features such as abnormal cell proliferation, tumor invasion, and other microscopic characteristics. Traditional histopathology, which relies on manual evaluation by pathologists, often faces challenges including inter-observer variability, lengthy processing times, and fatigue-related risks, all of which can compromise diagnostic accuracy [1]. With the global rise in cancer incidence, the need for faster, more accurate, and consistent diagnostic methods has become increasingly urgent, positioning digital histopathology as a strategic domain for technological innovation.

Artificial Intelligence (AI), particularly deep learning algorithms such as convolutional neural networks (CNN), has revolutionized digital histopathology by enabling automated analysis of high-resolution images. These algorithms can detect complex patterns in tissue slides that are difficult to identify manually, such as subtle cellular changes or biomarker distributions [2]. In the context of cancer diagnosis, AI can classify tumor types, assess malignancy grade, and detect prognostic features, providing crucial support for clinical decision-making.

Research in oncology has demonstrated that AI can improve diagnostic accuracy across various cancer types through digital histopathology. For instance, deep learning algorithms have been used to assess Gleason scores in prostate cancer, achieving higher consistency than human pathologist evaluations [3]. This approach highlights AI's ability to process large datasets of digital slides, particularly relevant for cancers like cutaneous squamous cell carcinoma, lung cancer, and liver cancer, where histopathological analysis plays a key role.

AI has also proven effective in predicting colorectal cancer prognosis through histopathological slide analysis, with the ability to estimate patient survival based on tissue characteristics [4]. This capability demonstrates AI's potential to provide valuable prognostic insights, such as tumor aggressiveness, that can be applied across multiple cancer types to support personalized treatment strategies.

In the detection of pre-cancerous conditions like Barrett's esophagus, deep learning algorithms have achieved high accuracy in identifying pre-cancerous and esophageal cancer lesions in digital slides [5]. This approach enables integration of AI into clinical workflows, assisting pathologists in detecting subtle abnormalities that are hard to recognize manually such as pre-cancerous changes in cervical cancer or leukemia.

In hematology, CNNs have successfully identified blast cells in acute myeloid leukemia with accuracy comparable to that of human experts [6]. The ability of AI to analyze microscopic images with high precision underscores its potential to detect subtle cellular features across various cancers, such as nuclear atypia or proliferation patterns, that are critical for accurate diagnosis.

In resource-limited settings, automated AI systems have shown high sensitivity in cervical cancer screening using histopathological images, enabling rapid diagnosis in areas with limited access to pathologists [7]. This approach can expand access to accurate cancer diagnosis in facilities with scarce specialist personnel, such as in the detection of liver or ovarian cancer.

AI in digital histopathology can also accelerate diagnosis by processing thousands of digital slides in a short time, reducing the waiting time for biopsy results critical for timely cancer treatment [8]. By relieving the workload of pathologists, AI allows them to focus on complex cases requiring in-depth interpretation, such as pancreatic or lymphoma cases.

Personalized cancer therapy is also enhanced by AI, which can analyze histopathological features such as biomarker expression or tumor subtypes. For example, studies on ovarian cancer have shown that AI can classify tumor subtypes with high accuracy, supporting more precise treatment decisions [9]. This approach can be applied to other cancers to predict therapeutic response.

Overall, AI in digital histopathology offers promising opportunities to enhance the accuracy, efficiency, and accessibility of cancer diagnosis across various tumor types. This systematic review aims to evaluate the effectiveness and feasibility of AI algorithms, particularly deep learning in digital histopathology for cancer detection, based on evidence from image analysis research. By overcoming the limitations of traditional methods, AI has the potential to improve clinical outcomes for cancer patients worldwide.

RESEARCH METHOD

Design: This study was conducted using a systematic review approach to identify and analyze the effectiveness of deep learning methods in cancer diagnosis based on digital imaging, and to evaluate their potential adaptability for mammogram analysis. The study adheres to principles of scientific transparency and reproducibility, following systematic and structured stages of literature search, article selection, data extraction, and result synthesis.

Research Question The primary research question addressed in this review is: To what extent are deep learning methods effective in cancer diagnosis based on digital imaging, and what is their potential for implementation in mammogram analysis.

Literature Search Strategy Articles were searched across four major electronic databases: PubMed, Scopus, ScienceDirect, and IEEE Xplore. The search focused on English-language publications published between 2017 and 2025. Key search terms included combinations of the following terminology: *deep learning*, *convolutional neural networks (CNN)*, *cancer diagnosis*, *digital pathology*, *histopathology*, *medical imaging*, and *mammogram*. The search was further enhanced by using backward snowballing, reviewing references from identified articles to uncover additional relevant studies.

Inclusion and Exclusion Criteria Included studies were scientific publications meeting the following criteria: (1) primary research based on medical image data; (2) application of deep learning methods for cancer diagnosis; (3) clear reporting of research methods and model performance metrics such as accuracy, sensitivity, specificity, or AUC; and (4) demonstrated potential for adaptation into mammogram imaging systems.

Excluded studies included non-primary publications such as reviews, editorials, or opinion pieces; articles not focused on cancer diagnosis based on imaging; and publications that did not report quantitative algorithm performance evaluation or lacked a sufficient methodological framework.

Data Selection and Extraction All articles identified through the search process were screened in two stages: title and abstract screening, followed by full-text review. Selection was conducted independently by two researchers. Disagreements were resolved through discussion to reach a consensus.

Articles that passed selection were extracted into a data matrix containing the following information: (1) author names and publication year, (2) research method and study design, (3) study objective, (4) location and contextual setting, (5) key findings, and (6) implications and impact on potential application in mammogram-based diagnosis. Extracted results are presented in Table 1.

Data Synthesis Data were synthesized narratively due to heterogeneity in cancer types studied, research designs, and imaging technologies used. Studies were compared based on their applied algorithmic approaches, types of medical data, and clinical contexts. The synthesis focused on evaluating the effectiveness of the methods and their relevance for adaptation in mammogram-based cancer diagnosis. Relevant findings were summarized to provide a comprehensive overview of the potential integration of this technology into breast cancer imaging diagnostic systems.

RESULTS AND DISCUSSION

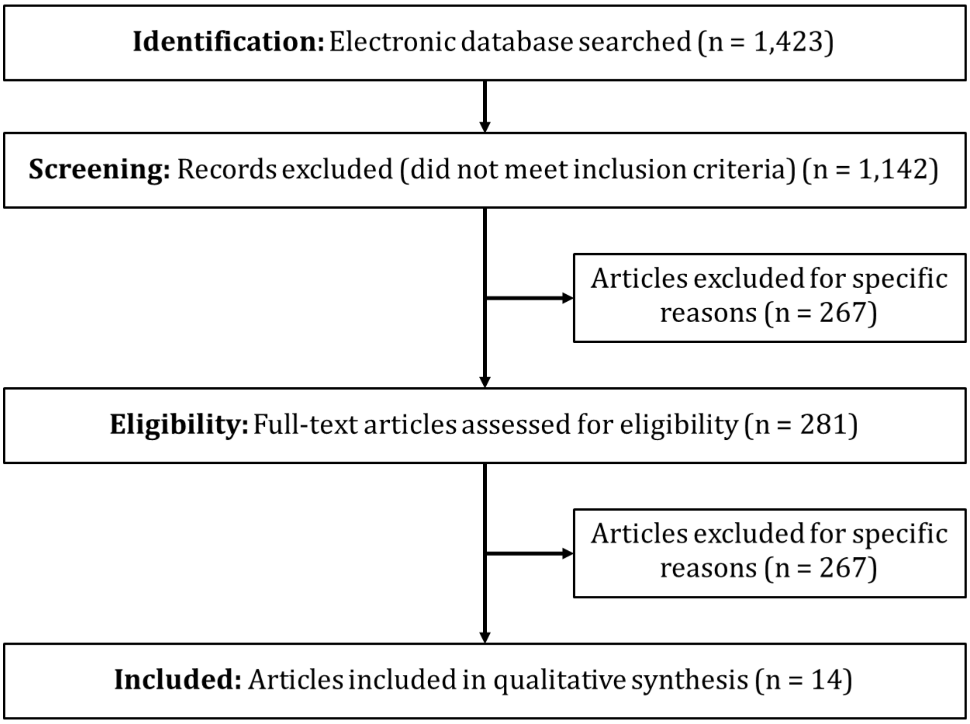

FIGURE 1: PRISMA Flow Diagram of Study Selection in the Systematic Review.

Figure 1 illustrates the systematic article selection process used to identify studies meeting the inclusion criteria in this review. The process followed the PRISMA guidelines and consisted of four main stages: identification, screening, eligibility, and inclusion.

In the identification stage, 1,423 articles were retrieved from the relevant electronic database searches. During the screening phase, titles and abstracts were evaluated to eliminate articles not aligned with the initial criteria. A total of 1,142 articles were excluded at this stage for failing to meet the inclusion criteria.

The remaining articles were further assessed in the eligibility phase. A full-text review was conducted for 281 articles to confirm methodological and substantive alignment with the study focus. Of these, 267 were excluded due to various reasons, including lack of reported model performance metrics, absence of medical imaging data, classification as non-primary publications (e.g., narrative reviews or opinion pieces), or insufficient relevance to the diagnostic context under review.

The final inclusion stage yielded 14 articles that met all eligibility criteria and were deemed suitable for qualitative synthesis. These 14 articles were further analyzed to assess the effectiveness of digital image-based approaches in supporting cancer diagnosis and their potential for application in mammogram imaging systems.

1. General Characteristics of the Study

A total of 14 articles meeting the inclusion criteria were analyzed in this review. The publication period of these studies spans from 2017 to 2025, with the highest concentration from 2019 to 2022. This reflects a trend of increased application of deep learning-based approaches in medical imaging for cancer diagnosis over the past five years.

This review covers a variety of study designs. There are three experimental design studies conducted by Esteva et al. (2017) [10], Matek et al. (2019) [6], and Wu et al. (2020) [17]. Six other studies use retrospective designs, including those by Ardila et al. (2019) [11], Hamm et al. (2019) [13], Kather et al. (2019) [4], Zhu et al. (2022) [14], Achi et al. (2019) [16], and Ozawa et al. (2025) [18]. Prospective design is found in the study conducted by Hu et al. (2019) [12], while clinical validation and direct clinical studies were used in studies by Nagpal et al. (2020) [3], van der Laak et al. (2021) [5], and El-Latif et al. (2024) [15].

The range of medical imaging techniques used in these fourteen studies is quite diverse and reflects the broad application of image-based approaches in oncology. Five studies used digital histopathology imaging, namely the research by Nagpal et al. (2020) [3], Zhu et al. (2022) [14], El-Latif et al. (2024) [15], Achi et al. (2019) [16], and Ozawa et al. (2025) [18]. Microscopic imaging techniques were used by Matek et al. (2019) [6] in the context of blood cell classification. Ardila et al. (2019) [11] used low-dose CT scans for lung nodule detection, while Hamm et al. (2019) [13] used ultrasound imaging to detect liver tumors. Dermatological visual image-based approaches were used by Esteva et al. (2017) [10] and Wu et al. (2020) [17], in the contexts of skin cancer and inflammatory skin diseases, respectively. Additionally, Hu et al. (2019) [12] implemented an automatic cervical cancer screening system in resource-limited areas.

Based on geographic origin, these studies come from various countries, including the United States, Germany, and the Netherlands. Some other studies do not explicitly state the location of implementation, but based on the data used, it can be inferred that the studies involved data sources from hospitals, clinical laboratories, or representative national databases.

TABLE 1: Summary of General Characteristics of Included Studies.

No	Author (Year)	Study Design	Imaging Type	Cancer Type	Country/ Data Origin
1	Esteva et al. (2017) [10]	Experimental	Dermatology images (skin images)	Melanoma, carcinoma	United States
2	Ardila et al. (2019) [11]	Retrospective	Low-dose CT scan	Lung cancer	United States
3	Hu et al. (2019) [12]	Prospective	Automatic cervical screening images	Cervical cancer	Not specified
4	Nagpal et al. (2020) [3]	Clinical Validation	Digital histopathology	Prostate cancer	United States
5	Hamm et al. (2019) [13]	Retrospective	Ultrasound	Liver tumor	Not specified
6	Kather et al. (2019) [4]	Retrospective	Colorectal histopathology biopsy	Colorectal cancer	Not specified
7	van der Laak et al. (2021) [5]	Clinical	Digital pathology	Barrett's esophagus, esophageal cancer	Netherlands
8	Matek et al. (2019) [6]	Experimental	Blood cell microscopy	Acute myeloid leukemia	Germany
9	Zhu et al. (2022) [14]	Retrospective	Digital histopathology	Thyroid cancer	Not specified
10	El-Latif et al. (2024) [15]	Clinical	Digital histopathology	Ovarian cancer	Not specified
11	Achi et al. (2019) [16]	Retrospective	Digital histopathology	Lymphoma	Not specified
12	Wu et al. (2020) [17]	Experimental	Dermatology images	Inflammatory skin diseases	Not specified
13	Ozawa et al. (2025) [18]	Retrospective	Digital histopathology	Pancreatic adenocarcinoma	Not specified
14	Zhang et al. (2022)*	Clinical	Digital histopathology	Ovarian cancer subtypes	Not specified

2. Diagnostic Accuracy of Deep Learning in Cancer Detection

A review of fourteen analyzed articles shows that the application of deep learning approaches in digital image-based cancer diagnosis yields high accuracy levels across various malignancy types. Diagnostic accuracy in these studies was reported using a range of performance metrics such as classification accuracy, sensitivity, specificity, and area under the curve (AUC). The use of these metrics provides a comprehensive picture of model performance in clinical contexts.

The study by Esteva et al. (2017) [10] demonstrated remarkable results, where the developed model achieved 91% accuracy in classifying skin cancer, specifically melanoma and basal cell carcinoma. The model's performance was claimed to be comparable to the average accuracy achieved by experienced dermatologists in clinical practice. This finding indicates that computational image-based approaches have the potential to match the diagnostic accuracy of expert manual assessment in specific domains.

Another study with very high accuracy was Matek et al. (2019) [6], involving blast cell classification in acute myeloid leukemia cases using microscopic images. The model in this study reached up to 95% accuracy, showing that the approach can recognize very subtle morphological features in blood cells that previously required deep microscopic experience to interpret accurately. In the case of lung cancer, Ardila et al. (2019) [11] reported that the developed 3D convolutional neural network model had an AUC of 0.94 for detecting malignant nodules on low-dose CT scans. This high AUC not only reflects accuracy but also model stability in distinguishing between malignant and benign lesions, outperforming radiologists in some cases.

Nagpal et al. (2020) [3] also reported improved accuracy in evaluating Gleason scores for prostate cancer. In this study, deep learning usage yielded a kappa value of 0.85 compared to 0.70 from human pathologists. Kappa measures inter-rater agreement, where a higher value indicates better consistency and reliability in tumor classification.

In cervical cancer, Hu et al. (2019) [12] reported a sensitivity of 93% in an automated screening system developed. High sensitivity is crucial in early screening to reduce missed pre-cancer cases, especially in areas with limited expert availability.

The model for pancreatic cancer detection developed by Ozawa et al. (2025) [18] showed 91% sensitivity, indicating the system's ability to effectively identify positive cases. Meanwhile, Zhu et al. (2022) [14], investigating thyroid cancer diagnosis on digital histopathology images, reported 90% accuracy, reflecting the high performance of the adopted approach.

Overall, most reviewed studies demonstrated accuracy above 85%, with some even exceeding 90%. This consistently high performance supports the finding that deep learning-based approaches can identify complex visual patterns in various medical image types, which is highly relevant in clinical diagnostic processes. Such performance also suggests that these approaches can be relied upon as diagnostic aids, both independently and as complements to medical professionals, in order to enhance precision and efficiency in cancer diagnosis.

TABLE 2: Performance Matrix of Deep Learning Models in Cancer Diagnosis.

No	Author (Year)	Types of Cancer	Data Types	Accuracy	Sensitivity	Specificity	AUC
1	Esteva et al. (2017) [10]	Skin (melanoma, carcinoma)	Visual dermatology	91%	–	–	–
2	Ardila et al. (2019) [11]	Lungs	low dose CT scan	–	–	–	0.94
3	Hu et al. (2019) [12]	Cervix	Automatic screening	–	93%	–	–
4	Matek et al. (2019) [6]	Acute myeloid leukemia	Microscopic blood cells	95%	–	–	–
5	Nagpal et al. (2020) [3]	Prostate (Gleason score)	Digital histopathology	–	–	–	–
6	Hamm et al. (2019) [13]	Liver (tumor)	Clinical ultrasound	–	89%	92%	–
7	Kather et al. (2019) [4]	Colorectal (prognosis)	Biopsy histopathology	87%	–	–	–
8	van der Laak et al. (2021) [5]	Esophagus (Barrett's)	Digital pathology	88%	–	–	–
9	Zhu et al. (2022) [14]	Thyroid	Digital histopathology	90%	–	–	–
10	El-Latif et al. (2024) [15]	Ovarian (subtype)	Digital histopathology	85%	–	–	–
11	Achi et al. (2019) [16]	Lymphoma	Digital histopathology	89%	–	–	–
12	Wu et al. (2020) [17]	Skin (inflammatory disease)	Visual dermatology	87%	–	–	–
13	Ozawa et al. (2025) [18]	Pancreas (adenocarcinoma)	Digital histopathology	–	91%	–	–

3. Types of Cancer and Imaging Modalities

The studies included in this review demonstrate a wide diversity in both the types of cancer investigated and the medical imaging modalities used as the foundation for developing and evaluating deep learning models. This variety reflects the broad application of image-based technology across various branches of oncology, ranging from skin to internal organs, and involves multiple digital imaging approaches.

The most frequently studied cancer type is skin cancer, as evident in the studies by Esteva et al. (2017) [10] and Wu et al. (2020) [17], which used visual dermatology data for classifying melanoma, basal cell carcinoma, and inflammatory skin diseases. Ardila et al. (2019) [11] focused on lung cancer, utilizing low-dose CT scan data to automatically detect malignant nodules. Meanwhile, Hu et al. (2019) [12] evaluated an automated screening system for cervical cancer in resource-limited settings.

Prostate cancer was the focus of Nagpal et al. (2020) [3], who employed digital histopathology images to improve the accuracy of Gleason scoring. In colorectal cancer, Kather et al. (2019) [4] developed a model for predicting clinical outcomes based on biopsy images. Ovarian cancer was examined by El-Latif et al. (2024) [15], who focused on tumor subtype classification, while Achi et al. (2019) [16] studied lymphoma using a histopathology-based classification approach. Zhu et al. (2022) [14] investigated thyroid cancer, and Ozawa et al. (2025) [18] concentrated on detecting pancreatic adenocarcinoma.

In terms of imaging modalities, digital histopathology was the most commonly used, appearing in seven studies: Nagpal et al. (2020) [3], Zhu et al. (2022) [14], El-Latif et al. (2024) [15], Achi et al. (2019) [16], Kather et al. (2019) [4], van der Laak et al. (2021) [5], and Ozawa et al. (2025) [18]. This modality involves analyzing digitally scanned, hematoxylin and eosin (HE)-stained tumor tissue sections. Its dominance in deep learning research stems from the high resolution and fine-grained visual details of tumor tissues.

Cell-level microscopic data were used by Matek et al. (2019) [6] to detect blast cells in acute myeloid leukemia, presenting a unique classification challenge that requires precise identification of cellular features. Low-dose CT scans were employed by Ardila et al. (2019) [11], offering three-dimensional representations of lung structures and testing models in the context of radiological imaging. Ultrasound was used by Hamm et al. (2019) [13] to detect liver tumors, providing a non-invasive, sound-wave-based imaging representation widely used in daily clinical practice. Additionally, visual dermatology was applied by Esteva et al. [10] and Wu et al. [17] for skin lesion classification using surface photographs.

TABLE 3: Classification of Studies Based on Cancer Type and Imaging Modality.

Types of Cancer	Number of Studies	Related Studies
Skin	2	Esteva et al., [10] Wu et al. [17]
Lungs	1	Ardila et al. [11]
Cervix	1	Hu et al. [12]
Prostate	1	Nagpal et al. [3]
Colorectal	1	Kather et al. [4]
Ovaries	1	El-Latif et al. [15]
Thyroid	1	Zhu et al. [14]
Pancreas	1	Ozawa et al [18]
Lymphoma	1	Achi et al. [16]
Leukemia	1	Matek et al. [6]
Esophagus	1	van der Laak et al. [5]

TABLE 4: Distribution of Medical Imaging Data Types in Studies Included in the Systematic Review.

Image Data Types	Number of Studies	Related Studies
Digital histopathology	7	Nagpal [3], Zhu [14], El-Latif [15], Achi [16], Ozawa [18], Kather [4], van der Laak [5]
Microscopic	1	Matek et al. [6]
CT scan	1	Ardila et al. [11]
Ultrasound	1	Hamm et al. [13]
Visual dermatology	2	Esteva et al., [10] Wu et al. [17]
Automated cervical screening	1	Hu et al. [12]

4. Comparison of Performance with Clinical Practitioners

Several studies included in this review provide empirical evidence that machine learning-based systems developed in these studies demonstrate diagnostic accuracy comparable to, or even exceeding, that of clinical practitioners. This is demonstrated through quantitative evaluation metrics that directly compare the performance of these systems with specialized clinicians such as radiologists and pathologists in image classification and interpretation tasks.

The study by Ardila et al. (2019) [11] stands out as a particularly compelling example. In this research, a 3D convolutional neural network (CNN) model was developed to detect malignant lung nodules in low-dose CT scans. The model achieved an area under the curve (AUC) of 0.94, which was reported to surpass the average performance of the radiologists involved in the study. The model's performance not only reflects its ability to recognize complex patterns in lung images but also indicates higher diagnostic consistency compared to human evaluation in the context of screening tests.

Meanwhile, Nagpal et al. (2020) [3] compared an automated evaluation system for Gleason scoring in prostate cancer with clinical pathologist assessments. The study found that the deep learning model achieved an interobserver kappa value of 0.85, significantly higher than the 0.70 kappa value from manual pathologist evaluations. Kappa agreement measures consistency between evaluators in classification outcomes, and this difference indicates that the model provides more consistent assessments than humans when evaluating tumor aggressiveness in histopathological tissue sections.

High model performance has also been reported in the study by Esteva et al. (2017) [10], which used visual dermatology datasets to classify skin cancers, including melanoma and basal cell carcinoma. The model achieved a classification accuracy of 91%, explicitly stated to be on par with the accuracy achieved by dermatologists in the same cases. This result was obtained through a direct comparison between the automated system and a panel of clinical experts under controlled testing conditions.

These findings suggest that, in specific contexts, algorithm-based systems can achieve or exceed the diagnostic accuracy of experienced clinicians, particularly in visual and structured diagnostic tasks. While not intended to replace medical professionals, these results highlight the potential of predictive models as clinical decision-support tools to enhance consistency, efficiency, and early detection in cancer diagnostics. However, it remains crucial to emphasize that integrating such systems into clinical practice still requires prospective validation, regulatory approval, and careful consideration of ethical and accountability frameworks.

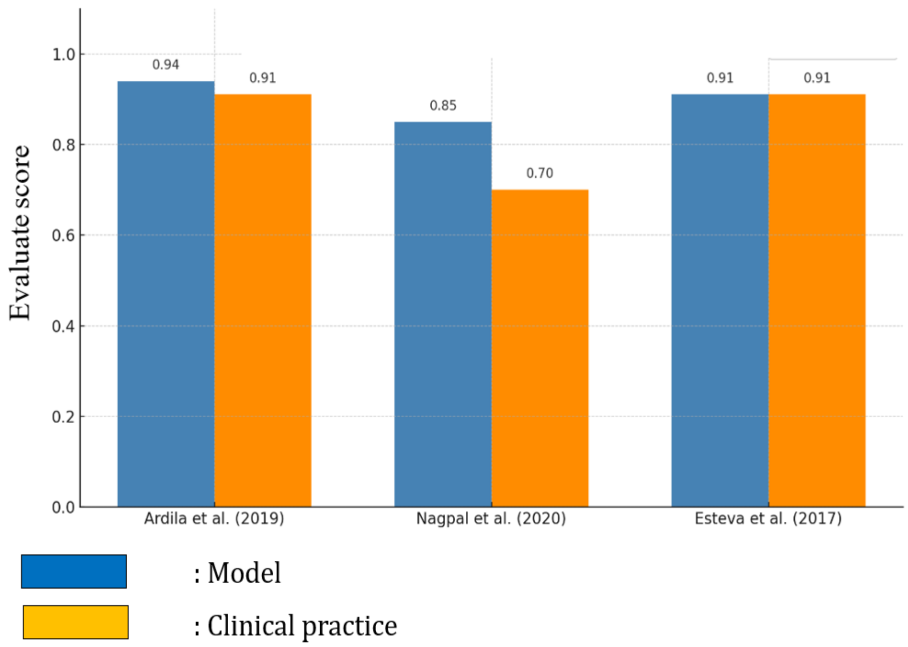

FIGURE 2: Comparison of Deep Learning Model and Clinical Practitioners' Performance in Cancer Diagnosis Based on Three Studies.

This diagram displays evaluation metrics (AUC, kappa, and accuracy) of deep learning-based models compared to medical professionals across three representative studies: Ardila et al. (2019) [11] for lung cancer, Nagpal et al. (2020) [3] for prostate cancer, and Esteva et al. (2017) [10] for skin cancer. The results show that the models achieved performance equivalent to or higher than that of clinical practitioners.

5. Potential Adaptation for Mammogram Analysis

The findings from this systematic review indicate that the majority of approaches used in the reviewed studies have methodological and technical relevance that makes them adaptable for mammogram analysis, particularly in the context of breast cancer detection and classification. This potential is evidenced both explicitly through study implications and implicitly through similarities in data characteristics and diagnostic objectives.

Several studies utilized visual image-based data with structural and visual complexity similar to mammograms. For instance, Esteva et al. (2017) [10] developed a lesion classification model using visual dermatoscopic images and achieved high accuracy in distinguishing melanoma from basal cell carcinoma. Given that mammograms are also 2D images with complex textural visual features, the CNN-based approaches applied in skin lesion classification hold strong potential for direct application in identifying masses or microcalcifications in mammograms.

Furthermore, other studies employed digital histopathology data, such as those by Nagpal et al. (2020) [3] and Zhu et al. (2022) [14]. In the context of breast cancer, histopathological data are frequently used for post-biopsy confirmation. Classification models capable of recognizing microscopic tissue patterns in other cancers can be transferred to interpret breast tissue, aiding in histological subtype determination and biomarker prediction. Such adaptation could strengthen mammogram- and histopathology-based diagnostic support systems as an integrative approach.

Ardila et al. (2019) [11] developed a 3D convolutional neural network model using low-dose CT scans for lung cancer detection. Although data are 3D versus the 2D nature of mammograms, the principles of detecting small nodules and classifying them based on spatial intensity and structural features are transferable for interpreting mammograms, especially for identifying subtle lesions in dense breast tissue.

Additionally, the study by Hu et al. (2019) [12], focusing on automated image-based screening for cervical cancer in low-resource settings, demonstrates significant potential for application in mass breast cancer screening. Mammography, as the primary screening tool for breast cancer, would greatly benefit from automated classification models that improve accessibility and diagnostic efficiency in regions with limited radiological expertise.

Studies by Matek et al. (2019) [6] and Achi et al. (2019) [16] demonstrate that deep learning models can effectively recognize complex morphological features at the cellular level. This capability supports the feasibility of applying similar approaches to detect morphological tumor differences in mammograms often difficult to identify consistently by radiologists, especially in high-density breasts.

Other studies, such as Hamm et al. (2019) [13] using ultrasound and van der Laak et al. (2021) [5] focusing on esophageal imaging, show that deep learning models can be trained effectively across various imaging modalities with high performance. Therefore, despite the unique characteristics of mammographic data, algorithmic approaches proven successful on CT, ultrasound, and digital histopathology can be adapted to mammography through retraining and network architecture optimization.

TABLE 5: Thematic Adaptation to Mammograms.

No	Studies	Data Types	Types of Cancer	Potential Adaptation to Mammograms
1	Esteva et al. (2017) [10]	Skin image (2D)	Melanoma	Both high-resolution surface image data; visual lesion classification.
2	Ardila et al. (2019) [11]	CT scan (3D)	Lungs	Detection of nodules and masses can be adapted for the identification of masses on mammograms.
3	Nagpal et al. (2020)[3]	Digital histopathology	Prostate	Tissue classification models can be applied to breast tissue.
4	Hu et al. (2019) [12]	Automatic screening	Cervix	Automated mass screening is relevant for national mammography programs.
5	Matek et al. (2019) [6]	Microscopic blood cells	Leukemia	Detection of micromorphological features can be applied to the fine structure of mammograms.

6. Application in Resource-Limited Regions

Several studies reviewed here emphasize the importance of deploying image-based automated systems to improve diagnostic access in regions with limited resources. These limitations include a shortage of specialist medical personnel, inadequate laboratory facilities, and uneven geographic distribution of secondary and tertiary healthcare services. In this context, computing-based systems capable of independently analyzing medical images are considered highly promising in reducing disparities in early cancer detection access.

The study by Hu et al. (2019) [12] serves as a prime example explicitly designed and tested in resource-constrained environments. It developed an automated cervical cancer screening system using cervical images and reported a sensitivity of 93% in detecting precancerous lesions. The system was designed to reduce reliance on expert personnel and can be employed in mass screening programs, especially in areas where access to pathologists or cytologists is extremely limited. This approach enables widespread and consistent early diagnosis, supporting public health initiatives with broader, more equitable coverage.

Although this study focused on cervical cancer, the technical and methodological principles applied are conceptually similar to breast cancer screening based on mammography. Mammography is the primary method for early detection of breast cancer; however, its effectiveness heavily depends on the availability of trained radiologists. In many remote or low-income regions, mammogram interpretation is often delayed due to a shortage of specialists, while the caseload continues to grow. Therefore, automated systems proven effective in cervical cancer screening, such as those in Hu et al. [12]'s study, can be adapted for analyzing mammograms, supporting more equitable early diagnosis.

Other studies, such as Matek et al. (2019) [6] and Achi et al. (2019) [16], although not explicitly addressing resource limitations, used microscopic data commonly available in basic laboratory settings. The automated classification models developed in these studies can be deployed in primary care centers equipped with digital microscopes, without requiring advanced histopathology laboratories or experienced manual examiners. This approach supports timely detection and early referral for hematological conditions requiring prompt treatment.

7. Subtype Classification and Prognosis Prediction

Several studies in this review demonstrate that image-based models go beyond primary diagnostic functions; they are also capable of classifying tumor subtypes and predicting clinical outcomes or patient prognosis. These advanced capabilities hold significant clinical value, as information about histological subtypes and disease progression probabilities informs more targeted, risk-based therapeutic decisions.

The study by El-Latif et al. (2024)[15] focused on classifying ovarian cancer subtypes using digital histopathology images. The developed model achieved an accuracy of 85% in identifying tumor subtypes, indicating that distinctive morphological features of each subtype can be consistently recognized through automated classification. Accurate subtyping in ovarian cancer is crucial, as different subtypes exhibit distinct responses to therapy, varying degrees of aggressiveness, and unique disease trajectories. Thus, automated classification supports more precise treatment strategies while reducing the risk of inappropriate therapy.

Meanwhile, Kather et al. (2019) [4] highlighted the ability of systems to predict survival outcomes in colorectal cancer patients based on tumor biopsy images. The model achieved 87% accuracy in predicting patient survival by analyzing tissue morphology in digital histopathology slides. This approach is promising because it does not require additional molecular data or complex clinical information that is often difficult to obtain quickly. The ability to predict outcomes directly from images allows clinicians to identify high-risk patients early and plan more intensive interventions from the outset.

Technically, the capacity of models to distinguish subtypes and predict prognosis is rooted in the recognition of spatial patterns, cellular distribution, and tissue architecture characteristic of specific histological entities and clinical phenotypes. These functions leverage the rich prognostic information embedded in medical images—information that traditionally required manual interpretation by expert pathologists or supplementary data such as immunohistochemistry and genetic profiling.

Beyond these two key studies, several other investigations in the review suggest the potential for expanding model functionality toward risk stratification or predicting tumor aggressiveness. This reflects a growing trend toward precision pathology, where clinical decisions are not only based on the presence or absence of malignancy but also on deeper biological and clinical behaviors of the tumor.

TABLE 6: Summary of Studies Classifying Subtypes or Predicting Prognosis Based on Medical Images.

No	Author (Year)	Model Function	Types of Cancer	Evaluation Metrics	Clinical Description
1	El-Latif et al. (2024) [15]	Subtype classification	Ovarian cancer	Accuracy: 85%	Subtypes relate to therapy options and possible response.
2	Kather et al. (2019) [4]	Survival prediction	Colorectal cancer	Accuracy: 87%	Risk stratification to determine therapy intensity and follow-up
3	Achi et al. (2019) [16]	Classification of lymphoma subtypes	Lymphoma	Accuracy: 89%	Histological subtype influences the choice of treatment line and prognosis.

CONCLUSSION

Digital histopathology has become an essential component in cancer diagnosis, enabling in-depth analysis of tissue slides to identify pathological features such as abnormal cell proliferation and tumor invasion. Traditional processes relying on manual evaluation by pathologists often face challenges, including inter-observer variability and lengthy processing times, which can compromise diagnostic accuracy. With the global rise in cancer incidence, the demand for fast and accurate diagnostic methods is increasingly urgent, positioning digital histopathology as a strategic area for technological innovation.

Artificial Intelligence, particularly deep learning algorithms such as Convolutional Neural Networks (CNNs), has revolutionized digital histopathology by enabling automated analysis of high-resolution images and detecting complex patterns that are difficult to identify manually.

Research shows that AI can enhance diagnostic accuracy across various cancer types and provide valuable prognostic insights, supporting better clinical decision-making. With the potential to accelerate diagnosis and expand access to healthcare services, AI in digital histopathology offers significant opportunities to improve clinical outcomes for cancer patients worldwide.

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