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AI in Oncology: A Review of Deep Learning-Based Approaches for Women's Cancer Diagnosis

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***Keywords*— Deep Learning, Women's Cancer Diagnosis, Breast Cancer, Cervical Cancer, Ovarian Cancer, CNN, Medical Imaging, Histopathology.**

***Abstract*— *Cancer is among the leading causes of death among women worldwide and the most common types are breast, cervical, ovarian, and uterine cancers. It is crucial that these cancers be diagnosed early and accurately to help improve survival and treatment outcomes. Artificial intelligence (AI), with deep learning specifically, has come to be regarded as a transforming tool in the field of oncology, one that provides high diagnostic accuracy and automation with high efficiency. This review offers a comprehensive view of deep learning-based approaches for women's cancer detection and diagnosis, focusing on a variety of methodologies of AI applied in medical imaging, histopathology, and genomic analysis. The paperdiscusses several widely used deep learning architectures like CNNs, RNNs, transformer-based models, and hybrid techniques and their applications in identifying and categorizing various cancers in women. We also discuss some of the most important public datasets, performance metrics, and comparative evaluations of existing AI-driven diagnostic models. Even though there has been tremendous progress, data scarcity, model interpretability, ethical concerns, and integration into clinical workflows are critical barriers to adoption. The Paper also highlight emerging research trends, such as explainable AI, federated learning, and multi-modal fusion techniques, that aim to enhance the reliability and robustness of AI in oncology.This review synthesizes recent developments in an attempt to provide insights into the current landscape of AI-driven cancer diagnosis and identify future directions for research and clinical implementation. The findings point to the revolutionary potential of deep learning in the detection of women's cancers, but underscore the importance of interdisciplinary collaboration to overcome the limitations identified and translate AI advances into real-world healthcare solutions.*

I. INTRODUCTION

Cancer is one of the leading killer diseases among the female population with breast, cervical, ovarian and uterine cancers being its most common cancer types. Overall, global data on cancer reflect that breast cancers are a notable cause of the death toll across women, besides cervical cancer constitutes a major burden to public health, especially from low- to middle-income developing countries [1]. Detection of these cancers at an early stage and with precision can lead to improvement in survival, as the treatment becomes effective at the earliest. Conventional methods like mammography, Pap smears, biopsy examinations, and imaging techniques face the challenges of a high false-positive/false-negative rate, subjective interpretation, and availability issues in resource-limited settings [1].

Among these challenges are the emergence of artificial intelligence and deep learning; these are more transformative technologies with considerable promise that can enhance oncology in better diagnostic accuracy with reduced human error and speed [2]. Integration of artificial intelligence within the medical imaging of histopathological and genomic analyses paved ways for automated high-precision detection systems in the field of cancers, significantly bettering early detection and patient prognosis. Such an overwhelming volume of data in the health sector, techniques based on AI can very easily analyze intricate patterns that cannot even be noticed by human experts thereby helping the radiologists and the pathologists diagnose more reliably [2].

A. AI & Deep Learning in Oncology:

With AI and Deep Learning, much of the sector of healthcare is being changed today, with significant attention in Oncology. Deep learning models have shown excellent performance applied to a variety of architectures, including Convolutional Neural Networks [2], Recurrent Neural Networks, or even a mix of both models because they are typically really good in analyzing medical images, histopathological slides, and genomic data for the high accuracy in identifying cancerous lesions. These models can be learned for large amounts of datasets on patterns that indicate malignancies and thus reduce the dependency on manual interpretation, aiding in the enhancement of the efficiency of diagnosis [2].

AI has been applied very widely in detection of abnormalities in mammograms, Pap smear slides, ultrasound scans, and MRI images in women's cancer diagnosis. The CNN-based models such as ResNet, VGG, and EfficientNet score well on detecting breast cancers and cytology analysis through deep learning has improved in identifying cervical cancer from Pap smear samples [3]. Learning is multimodal, and integrating images with genomics data or clinical information makes it possible for better painting that would help give a clearer outline for cancer risks and its potential progression. Despite all these developments, several challenges have been faced, and they include the requirement for large annotated datasets, requirements for models to be interpreted, ethical considerations, and issues in incorporating this model into the clinical environment [3].

B. Scope & Objectives of the Review

This review of deep learning-based approaches in the diagnosis of women's cancers will provide an overview of the latest AI techniques applied to breast, cervical, ovarian, and uterine cancer detection, focusing on their methodologies, performance, and clinical implications [4]. Specifically, this review will try to answer the following research questions:

- What are the most effective deep learning models used in women's cancer diagnosis?
- How well do these AI models compare to traditional methods in terms of sensitivity and specificity and accuracy?
- The major datasets that are used for training and evaluation of AI-driven cancer detection systems
- Challenges and limitations to the integration of deep learning models in clinical use
- Future trends, new AI techniques that would advance women's cancer diagnosis

This paper will therefore review peer-reviewed journal articles, conference proceedings, and publicly available datasets from major repositories to ensure that the analysis is systematic and comprehensive. It will compare different approaches in deep learning and discuss challenges and possible solutions in implementing AI in clinical practice [4].

This review synthesizes existing research, identifies gaps, and aims at providing valuable insights for researchers, healthcare professionals, and policymakers about the transformative role of deep learning in women's oncology, paving the way for future innovations in AI-driven cancer diagnosis.

Overview of Women's Cancers and Diagnostic Challenges

A. Common Cancers in Women

Cancer is probably the world's most challenging health problem with the global women, which the four cancers- breast, cervical, ovarian, and uterine find place most frequently. Though the etiology, the potential risk factors, and treatments vary, these all share one common challenge: early detection has been proven to significantly increase chances of survival [5].

Breast cancer is the most frequent cancer among females and accounts for a significant part of deaths all over the globe. It involves an unregulated multiplication of cells within the mammary tissue and may be the result of a disorder in the ducts or the lobules. Genetic disorders like BRCA1 and BRCA2, hormonal imbalance, lifestyle, and age are common causes. There is early diagnosis via screening services such as mammography and ultrasound that has assisted in lowering deaths from this malignancy [5].It ranks one of the leading killer cancers in women, often in low- and middle-income countries. This cancer usually develops from pre-cancerous lesions that take several years, so the only way early detection can be achieved is through regular Pap smear tests and HPV testing. The incidence of this cancer has dramatically decreased in developed countries with vaccination against HPV [6].

Ovarian cancer has been referred to as a "silent killer" because this type of cancer is not symptomatic in the early stages, and therefore, it is challenging to detect at an early stage. The origin is ovarian or fallopian tube tissues, and usually, the diagnosis is established in an advanced stage when limited treatment options are available [7]. The most commonly utilized risk assessment and detection tools, such as CA-125 blood tests, transvaginal ultrasound, and genetic screening for BRCA mutations, lack specificity and sensitivity [7].

Uterine, or endometrial, cancer is the most common gynecological cancer in postmenopausal females. It starts on the lining of the uterus, and there is a high correlation between the condition and hormonal imbalances, obesity, and genetic predisposition. Most patients are diagnosed via endometrial biopsy, transvaginal ultrasound, and MRI scans. Unlike the ovarian cancer, uterine cancer often responds to symptoms early, such as abnormal vaginal bleeding, so early detection is much more feasible [8].

B. Existing Diagnostic Techniques

Early and accurate diagnosis is the key to the improvement of survival rates and decision-making in directing treatment for women's cancers. Several traditional methods of diagnosis have been used in clinical practice, ranging from imaging techniques to invasive biopsy procedures [9].

Medical Imaging Techniques

- **Mammography:** This remains the gold standard for breast cancer screening. It uses low-dose X-rays to detect abnormalities in breast tissue. However, its effectiveness is limited in dense breast tissue that may obscure tumors [8].
- **Ultrasound:** Used as a complementary method of mammography; this imaging procedure differentiates a solid tumor from fluid-filled cysts, mostly in young patients [8].
- **MRI:** Soft tissue images can be clearly identified; therefore, this modality is used primarily in at-risk patients and indeterminate cases where the result comes from a mammogram [8].
- **TVUS:** Can diagnose ovarian and uterine malignancies by direct imaging of reproductive organs through this type of ultrasound in real time [8].

Cytology and Biopsy-Based Techniques

- Pap Smear Test - A routine screening technique in cervical cancer, where cellular components are collected from the cervix and examined for abnormalities [9].
- HPV Testing identifies individuals infected with high-risk HPV strains, which are capable of causing cervical cancer [9].
- Fine Needle Aspiration Biopsy (FNAB) is an inpainfully carried out breast cancer investigation procedure whereby cells are obtained from a suspicious nodule.
- Core Needle Biopsy (CNB) is an investigation procedure that involves tissue removal; this is done to confirm the existence of cancer through histopathology examination.
- Endometrial biopsy: This serves to diagnose cervical cancer by assaying a fragment of the uterus lining [9].

C. Challenges

Improvements in all these methods will still face failure in early and timely detection; this is associated with the drawback of low and inadequate sensitivity or specificity and difficulties in excess of these methods [10].

- **High False Positives and False Negatives:** Mammography and ultrasound techniques often result in false positives or false negatives, which may lead to unnecessary biopsies or missed diagnoses. For instance, mammograms can obscure tumors in dense breast tissue, and Pap smear tests can miss early cervical abnormalities. AI-based deep learning models may be used to improve the accuracy of detection by finding minute patterns in medical images that are overlooked by human radiologists [10].

- **Issues of cost and accessibility:** Such advanced imaging technologies, such as MRI and molecular diagnostics, are very expensive, and in most cases, inaccessible in low-resource settings. A regular screening program remains inaccessible to most women of the low- and middle-income countries, and hence, chances are more to be diagnosed in the late stage of cancer. Inclusion of AI-based diagnostic tools may help fill the gaps with scalable, automated, and cost-effective solutions [10].
- **Need for automation and standardization:** Histopathology slides and medical images are time-consuming to interpret and can have inter-observer variability. It is not always possible to get expert opinion to arrive at an accurate diagnosis, especially in the periphery. AI-based models may be helpful to pathologists by auto-analyzing the images, standardizing the criteria, and eliminating human mistakes [10].
- **Data Quality and Integration Issues:** Many AI models require large, annotated datasets for training. Getting high-quality medical data is challenging due to privacy concerns, variations in imaging protocols, and inconsistent labeling. The emerging solutions that help in overcoming these barriers are federated learning and privacy-preserving AI techniques [10].
- **Ethical and Regulatory Challenges.** The use of AI in oncology is associated with ethical issues related to patient data protection, elimination of bias, and ensuring the transparency of algorithms used by the AI systems. Most importantly, AI systems need to be adopted in practice in a transparent manner, following laws and regulations.

These factors can revolutionize the detection of women's cancers by improving precision, reducing the cost, and allowing the early intervention to take place. However, for AI to be fully utilized, many challenges like data availability, clinical validation, and ethical issues need to be addressed. In the subsequent sections, we discuss the development of deep learning models for the enhancement of detection and diagnosis in women's cancers by discussing the strengths, limitations, and prospects of applying such models [10].

Deep Learning Techniques to Detect Cancer In Females

Deep learning has improved cancer detection and diagnosis in the field of oncology. It has been applied effectively in the analysis of histopathology slides, medical image analysis, and genetic data analysis using CNN-like models [11]. Thus, the AI-based solutions will allow researchers and clinicians to be more accurate and less delayed in diagnosis and earlier detection. This chapter discusses how deep learning is changing the detection process of breast, cervical, ovarian, and uterine cancers and the part of multi-modal learning in refining the accuracy of diagnosis [11].

A. Detection of Breast Cancer

CNN-based models have widely contributed to the improvement of breast cancer detection by efficiently evaluating mammograms, ultrasound images, and MRI scans. Several CNN architectures were used in finding malignant lesions by achieving a highly accurate detection using ResNet, VGG, EfficientNet, and DenseNet [11]. The hierarchal feature extraction in these medical images made it possible for the models to automatically classify between benign and malignant tumors. Techniques of transfer learning that carry over pre-trained models from large datasets to fine-tune on specific medical imaging datasets have also improved the performance, especially when annotated medical data is limited. Other techniques involving ensemble learning that pools multiple deep learning models together have also been used to increase robustness and generalization toward reducing false positive and false negative results. Such AI-backed CAD systems are actually being used currently in the clinical environment to support radiologists toward better decision making [11].

B. Cervical Cancer Diagnosis

Deep learning has significantly rendered analysis automation possible while analyzing Pap smears for diagnosing cervical cancer. Traditional Pap smear evaluation is error-prone and subject to inter-observer variability, but newer AI-based models, such as You Only Look Once (YOLO) and U-Net [12], have also been established for high-precision cell segmentation and classification of abnormal cervical cells. YOLO-based models detect and localize cervical abnormalities on cytology images, and the U-Net is a powerful image segmentation network that can delineate abnormal cell structure precisely. These have improved the sensitivity and reproducibility of cervical cancer screening, less reliance on subjective interpretation [12].

Deep learning is also employed in the diagnosis of HPV and risk stratification, in addition to Pap smear evaluation. HPV is the main etiologic agent for cervical cancer, and AI models are now trained to interpret genetic and molecular data for predicting the probability of a given person developing cervical cancer [13]. The AI-driven risk stratification model incorporates deep neural networks, combining information from patient history, imaging, and HPV genotype data in a more holistic way toward early detection and prevention.

C. Early Detection of Ovarian and Uterine Cancer

Ovarian and uterine cancers [14] are one of the most difficult to be diagnosed because it remains asymptomatic during the early stages. Histopathology and radiomics based on deep learning have now emerged as powerful tools in identifying malignant tissue patterns from biopsy slides and imaging modalities. CNNs and Vision Transformers (ViTs) are being used to classify histopathological images of ovarian and endometrial cancer, differentiate between different grades and subtypes of tumors. In radiomics, AI models apply feature images and features extracted from CT, MRI, and transvaginal ultrasound scans to detect subtle textural patterns that can indicate malignancy [14].

AI-driven radiomics models use deep learning to learn quantitative imaging biomarkers that have been helpful for the characterization of tumors and prognosis prediction. Unlike the traditional assessment of images in terms of the qualitative interpretation made, radiomics combined with deep learning presents data-driven approaches towards the improvement of early detection rates. Models based on anomaly detection with deep learning are in development to find rare and aggressive ovarian and uterine cancers subtypes, thus supporting personal treatment plans [14].

D. Multi-Modal Learning for Cancer Detection

This multi-modal learning methodology revolutionizes cancer diagnosis by taking images, genomics, and clinical data as an integrated view of disease progression. The AI model has so far concentrated only on one form of data, such as medical images, but a multi-modal deep learning system will combine more than one sources of information in order to achieve accuracy and reliability [15]. For example, incorporation of mammography data with information related to some genetic markers or histopathological slides, together with patient clinical history, dramatically improves the precision in breast-cancer diagnosis. Different types of multi-modal architectures such as Transformers, CNN-to-RNN-to-CNN are devised for improved learning across other modalities which is supposed to give more enhanced results for high precision diagnostic assessment [15].

Using the images from Pap smear, HPV genotyping, and patient demographics, AI models would be able to integrate more information to enhance the risk assessment of an entity-specific level with detailed personalization for targeted screening and intervention. In the case of ovarian cancer, advances that utilize multi-modal approaches through radiomics, molecular profiling, and clinical features can demonstrate established ability in predicting response to treatment and survival outcomes [15].

Multi-modal deep learning allows researchers to get closer to precision oncology tools that could help in the comprehensive and individualized approach towards diagnosis and management of cancer. Models improve detection accuracy, help with treatment planning and prognosis estimation, and aid in clinical decision support, which would enhance patient outcomes in women's oncology [15].

II. METHODOLOGY

The recent developments in deep learning-based techniques for the diagnosis of cancer in women will be thoroughly examined and summarized in this review paper using an organized manner. Finding pertinent literature, applying strict screening standards, and doing in-depth research on a few chosen studies are all part of the technique. Below is the step-by-step methodology applied to this review.

A. Databases/Resources

The following databases and journals are chosen as primary sources of literature, ensuring the best quality of research articles:

- IEEE Xplore
- Springer
- Elsevier
- Wiley Online Library
- PubMed and Medline
- Google Scholar

These sites are well-known for carrying very large collections of peer-reviewed studies on topics such as artificial intelligence, medical imaging, oncology, and deep learning.Furthermore, contributions from topmost conferences such as MICCAI: Medical Image Computing and Computer-Assisted Intervention, NeurIPS: Conference on Neural Information Processing Systems, and CVPR: Conference on Computer Vision and Pattern Recognition are also considered so that the best developments in deep learning for application in cancer diagnosis are covered.

B. Inclusion criteria

The review was conducted strictly following an inclusion criterion, thus only high-quality and relevant research papers were included. The choice was made based on the following parameters:

- **Time Frame:** The materials considered for this review were only those published over the last ten years, 2019–2024.However, earlier published articles were also considered if they included fundamental information that was essential to understand the current improvement.
- **Pertinence to Cancer Diagnosis:** The papers selected regarding the artificial intelligence-based diagnosis of cancer include studies based on deep learning regarding the detection of endometrial, breast, cervical, and ovarian cancers.The exclusion criteria include unrelated illness or general-purpose papers outlining the applicability of AI in healthcare without a specific oncology-related application.
- **Deep Learning Orientation:** The article covered studies that use deep learning techniques such as CNN, RNNs, Transformer architecture, and multi-model methods. Work on traditional learning models like decision trees or SVMs where no deep model has been introduced has not been included.
- **Medical Imaging and Multi-Modal Approaches :** Research that involved medical imaging techniques (e.g., mammograms, Pap smears, histopathology slides, MRI, CT scans) as well as multi-modal deep learning models that integrated imaging, genomics, and clinical data were considered. Those studies that did not involve image-based AI applications were excluded.

C. Key words

A targeted keyword strategy was deployed so that an efficient search for relevant studies was undertaken. The key words used for the literature search were:

- Women's cancer diagnosis:
- Deep learning in oncology
- AI-based breast cancer detection
- AI-based cervical cancer diagnosis
- Medical imaging and Deep Learning
- Convolutional Neural Networks (CNN) for detecting cancer
- Transformer models in medical diagnosis
- Multi-modal learning in oncology
- Radiomics and Deep learning

These above-mentioned keywords were combined with the Boolean operators-AND, OR -in a strategic way to refine the search and retrieve relevant literature.

D. Selection Procedure

The selection process was carried out in three stages:

Main Collection: First, a general search was conducted in the selected words using all identified databases. About 50 peer-reviewed articles were gathered. The other type of tracking used is citation tracking, which helps gather additional relevant papers.

Shortlisting: All the abstracts and titles of the shortlisted papers that were retrieved were reviewed based on the inclusion criteria. From the primary, 25 papers were selected with relevance to women's cancer detection, AI methodologies, and recent advancements in deep learning.

Final Review: A comprehensive review of the most impactful 15 papers was done, focusing on contributions to deep learning models, clinical validation, and innovative AI techniques for cancer diagnosis. These papers formed the basis of the in-depth discussion in this review.

It will keep the review contemporary and detailed concerning the use of deep learning to diagnose cancer among women and draw attention to their key advancement challenges, as well as research priorities in the area.

Table 1. Selection Process of Literature Review

Stage	Number of Papers	Description
Initial Collection	100	Papers identified through database searches and citation tracking using defined keywords.
Shortlisting	25	Papers reviewed for relevance based on inclusion criteria (deep learning models, medical imaging, AI-based cancer diagnosis).
Final Review	15	In-depth review of selected papers that focus on CNN-based models, transformer models, and multimodal AI for women’s cancer diagnosis.

E. Data Extraction

In the last stage, data extraction was conducted from all of the selected 15 papers focusing on the following key aspects:

- **Model Architectures:** Analyzed the deep learning architectures of cancer detection models that include CNN-based models such as ResNet, VGG, and EfficientNet, transformer-based models, and hybrid AI approaches.
- **Techniques and Methodologies:** The different AI techniques explored are transfer learning, ensemble learning, and multimodal AI models with clinical, imaging, and genomic data.
- **Medical Imaging and Multi-Modal Integration:** Researched how the different modalities, including radiological images like mammography, MRI, and CT scans, histopathology slides, and genomic data are fused for the better diagnosis of cancer. The strategies followed included early and late fusion.
- **Performance and Evaluation:** Compared performance metrics reported on different AI models and types of cancers, based on accuracy, sensitivity, specificity, and AUC-ROC values, that reflected their usefulness and clinical validity.

This methodological approach to the review aims to ensure an all-inclusive and updated survey of deep learning approaches for diagnosis in women's cancer, keeping in mind main advancements, difficulties, and possible future research ways.

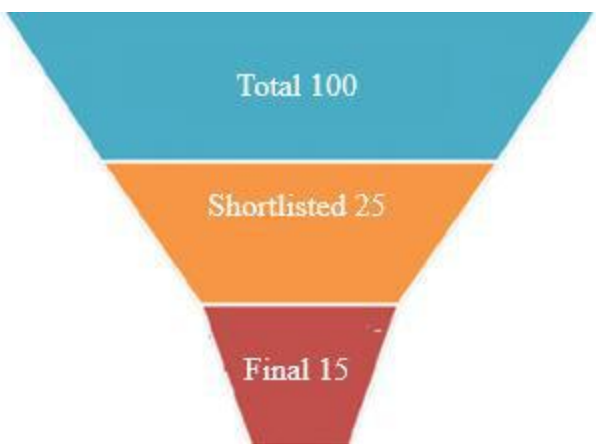

Fig.1. Funnel Diagram for Literature Review

III. LITERATURE REVIEW

The final selected papers for literature review are as follows,

Sureshkumar, V., et al. (2024) [16] proposed a hybrid model that integrates Convolutional Neural Network (CNN) with a pruned ensembled Extreme Learning Machine (HCPELM) to enhance the detection, segmentation and classification of breast cancer with an overall accuracy of 86% in the MIAS database, with better performance compared to benchmark deep-learning models. CNN layers were implemented to extract the spatial feature while HCPELM was used for classification, applying transfer learning to reduce the parameters while enhancing the precision in detection. This method improves early detection, making it a useful tool for healthcare practitioners.

Nafea, A. A., et al. (2024) [17] introduce a method combining one-dimensional CNN (1D CNN) for feature extraction with machine learning algorithms like XGBoost, random forests (RF), and support vector machines (SVM) to classify breast cancer as benign or malignant. Using the Wisconsin Breast Cancer dataset, their approach attained a test accuracy of 98.24%, demonstrating the potential of combining deep learning and machine learning to improve diagnostic reliability and reduce false positives.

Ajlouni, N. et al. (2024) [18] propose a hybrid approach to automatically stage TNM breast cancer by integrating CNNs, edge detection algorithms, and SOMs. With the use of the Duke Breast Cancer MRI dataset, the approach enhances the accuracy of staging up to 98% in comparison with the traditional CNN models. This approach clearly identifies the boundaries of the tumor and anatomical features, thus allowing for personalization in treatment plans, increased diagnostic accuracy, and minimized manual interpretation errors, thus benefiting both the patient and the medical staff.

Rani, N. D., &Arrama, M. B. (2024) [19] Presented an automated framework for the detection of ovarian cancer using Optical Coherence Tomography (OCT) in transgenic mice. The three neural network architectures used in the study were VGG-supported feed-forward, 3D CNN, and convolutional LSTM. Among them, convolutional LSTM performed the best with a mean AUC of 0.86. This pioneering research will have the potential to transfer OCT-based diagnostic tools from animal models to humans with a potential for earlier intervention in ovarian cancer.

Rajesh, P., et al. (2024) [20] uses 3D CNN in order to detect metastatic ovarian tumors by examining the MRI scans with the detection accuracy of 98.76% on Ovarian Bevacizumab Response dataset. Compared to 2D-CNNs, it allows for the capturing spatial as well as temporal features present on MRI scans. Additionally enriched with data augmentation, enhanced early detection and high quality diagnostic accuracy make way with huge clinical potential that leads patients towards better outcomes.

Behera, S. K., et al. (2024) [21] propose a robust classification method for ovarian cancer subtypes, integrating EfficientNet-B0 for feature extraction with a fine-grained k-nearest neighbor (KNN) classifier. Using the UBC-OCEAN dataset of histopathological images, the model achieves 100% accuracy in validation and testing. High AUC and likelihood ratio values highlight its diagnostic efficacy, positioning the model as a promising tool for precision medicine in ovarian cancer research.

Das, A., et al. (2024, January) [22] evaluate 18 CNN models for the detection of ovarian cancer based on histopathological images, whereby the darknet19 model outperformed all. Metrics include average accuracy 99.79%, sensitivity 99.73%, and specificity 99.84%, while the computation time was 9.58 seconds. The study thereby points out that deep learning may play an important role in improving ovarian cancer diagnosis, especially to identify subgroup candidates, with immense implications in clinical practice.

Ziyambe et al. (2023) [23] Ovarian cancer is one of the types of cancers that cause the deaths of women as the fifth most common cause; it has an issue of delayed diagnosis, particularly stages III and IV, with vague initial symptoms. Current diagnosis methods include biomarkers, biopsy, and imaging, which present some drawbacks in terms of being subjective, with variability, and extended testing time. This paper introduces CNN, trained by histopathological images, improving accuracy in diagnostic terms. Achieving 94% accuracy accuracy and being proper in 95.12% of cancer cases and 93.02% in healthy specimens, the research unveils considerable strength of using CNN to exhibit very low levels of human mistakes and efficiency especially with regard to determination of the existence of ovarian cancer. Further research, based on the results obtained should be utilized in taking it into more potent configurations.

Martinez, R. G., & van Dongen, D. M. (2023)[24] Deep learning, or DL, has been highly applied to breast cancer screenings with images data. This research focuses on using DL for the prescreening of cancer with heterogeneous data: patient demographics, blood biomarkers, and risk assessments based on meta-analysis. Using feature selection on a data set of 64 breast cancer patients and 52 healthy women, DL models outperformed traditional machine learning methods, decreased false negatives, and provided better predictions. It underscores DL's promise as a non-invasive, radiation-free, and cost-effective tool for the early detection of cancer.

Younezade, N., et al. (2023)[25] Cancer is still the second cause of death for women due to cancer; deaths are expected to grow to 400,000 cases per year in 2030 if proper management is not adopted. Early detection includes Pap smear and colposcopy, yet manual screening has a very high tendency of error; hence, this paper conducts a review on DL-based CAD techniques that can automate segmentation and classification of cervical cytology and colposcopy images for high accuracy. This discussion focuses on AI-based solutions particularly in low-resource areas and DL architectures with their respective applications in CC screening.

Humayun, M., et al. 2023 [26]. Even though breast cancer remains one of the leading causes of death, prognosis today is more and more dependent on gene expression analysis and deep learning-based imaging techniques. This paper describes a transfer learning approach using the InceptionResNetV2 model for risk prediction of breast cancer. This yielded an accuracy of 91% in the experimental results on a breast cancer dataset, thus showing the potential of the model to enhance risk assessment. The study, therefore, demonstrates the role that DL may assume in automating medical imaging and enhancing the detection and risk prediction of breast cancer.

Al Fryan, L. H., et al. (2023) [27] Histological classification of breast cancer is important for prognosis but suffers from inter-observer variability. The paper uses CNNs to automate histological classification with accuracy, reproducibility, and a reduction in bias. The model filters low-representation tumor cell images and classifies them very efficiently. Results suggest that the CNN-based classification can improve diagnostic reliability, particularly in remote areas where medical expertise is limited.

Xue, P., et al. (2022) [28] This meta-analysis reviews the diagnostic performance of DL algorithms for breast and cervical cancer. For 35 studies, pooled sensitivity was 88%, specificity was 84%, and AUC was 0.92, indicating DL was comparable to human clinicians. Study design biases might inflate algorithm effectiveness. Standardized research methodologies are recommended to ensure the reliability of DL-based cancer detection models.

Allugunti, V. R. (2022) [29] Breast carcinoma is the most common cancer case in the world, leading to nearly 900,000 deaths yearly. Early and accurate diagnosis improves survival rates markedly. This paper presents a CAD system based on the CNN, Support Vector Machine (SVM), and Random Forest (RF) that shall classify the type of breast cancer into three classes: cancerous, non-cancerous, and no cancer. This study shows that the preprocessing of mammography images increases the accuracy of classification.

Wang, Y., et al. (2022)[30] The Nottingham histological grade (NHG) is an important prognostic factor for breast cancer, but more than 50% of patients are classified to the intermediate-risk grade 2 category, thereby limiting its clinical utility. A DL-based model for stratifying NHG 2 cases by whole-slide histopathology images is developed and mentioned as DeepGrade. DeepGrade differentiates the high and low risk cases that match the NHG 1 and NHG 3 tumor characteristics. The results show that DeepGrade is cost-effective in producing a good prognosis, especially with no need to perform any molecular profiling in breast cancer risk assessment.

Table 1. Literature Review Findings

Author Name (Year)	**Main Concept**	**Findings**	**Limitations**
Sureshkumar, V., et al. (2024)	Hybrid CNN and pruned ensembled ELM for breast cancer detection	Achieved 86% accuracy on MIAS dataset; improved precision with transfer learning	Performance compared only with benchmark deep-learning models, not broader ML techniques
Nafea, A. A., et al. (2024)	1D CNN with ML classifiers for breast cancer classification	Achieved 98.24% accuracy on Wisconsin Breast Cancer dataset	Limited to structured datasets, lacks evaluation on real-world clinical images
Ajlouni, N. et al. (2024)	Hybrid CNN, edge detection, and SOMs for TNM breast cancer staging	98% accuracy on Duke Breast Cancer MRI dataset, improved staging and personalization	Focuses only on TNM staging, applicability to other staging methods unclear
Rani, N. D., & Arrama, M. B. (2024)	Automated ovarian cancer detection using OCT and deep learning	Convolutional LSTM outperformed other models with AUC of 0.86	Study limited to transgenic mice; requires validation in human clinical settings
Rajesh, P., et al. (2024)	3D CNN for metastatic ovarian tumor detection	Achieved 98.76% accuracy on Ovarian Bevacizumab Response dataset	Study relies on a single dataset, may not generalize well to diverse populations
Behera, S. K., et al. (2024)	EfficientNet-B0 with KNN for ovarian cancer subtype classification	Achieved 100% accuracy on UBC-OCEAN dataset	Unusually high accuracy suggests possible overfitting or dataset bias
Das, A., et al. (2024)	Comparison of 18 CNN models for ovarian cancer detection	Darknet19 achieved highest accuracy (99.79%), sensitivity (99.73%), specificity (99.84%)	High accuracy but lacks external validation and clinical applicability testing
Ziyambe et al. (2023)	CNN-based ovarian cancer diagnosis from histopathological images	94% accuracy, with 95.12% sensitivity and 93.02% specificity	Limited dataset size, lacks comparison with non-DL techniques
Martinez, R. G., & van Dongen, D. M. (2023)	DL for heterogeneous breast cancer screening	Improved accuracy and reduced false negatives using patient demographics and biomarkers	Small dataset (64 patients, 52 healthy), needs larger validation
Younezade, N., et al. (2023)	DL-based CAD for cervical cancer screening	Highlights AI's role in automating segmentation and classification	Focused on low-resource areas; lacks discussion on model fairness and bias
Humayun, M., et al.	InceptionResNetV2 for breast	Achieved 91% accuracy using	Limited dataset and no

(2023)	cancer risk prediction	gene expression and imaging data	external clinical validation
Al Fryan, L. H., et al. (2023)	CNN-based histological classification of breast cancer	Improved classification accuracy, reducing inter-observer variability	No comparison with traditional pathology methods
Xue, P., et al. (2022)	Meta-analysis of DL in breast and cervical cancer diagnosis	Pooled sensitivity 88%, specificity 84%, AUC 0.92	Study design biases may overestimate algorithm effectiveness
Allugunti, V. R. (2022)	CNN, SVM, and RF for breast cancer classification	Improved classification with image preprocessing	Does not explore deep learning-only approaches for comparison
Wang, Y., et al. (2022)	DL-based NHG stratification for breast cancer prognosis	Developed DeepGrade model to differentiate high and low-risk cases	Study focuses only on NHG 2 cases, missing broader patient spectrum

Research gaps Discussion

Despite the significant strides made in deep learning-based cancer detection and classification, there are still many gaps in research. Many studies are able to attain high accuracy with specific datasets such as MIAS, Wisconsin Breast Cancer, and UBC-OCEAN but lack external validation on diverse, real-world clinical data, hence limiting generalizability. In addition, although hybrid models that combine CNNs with machine learning classifiers, for example, XGBoost, KNN, and RF, have been shown to be promising, their comparative advantages over pure deep learning architectures remain underexplored. The issue of the bias in dataset, especially about studies reporting very high accuracy figures, raises alarm about overfitting and requirement for robust techniques of cross-validation. Furthermore, current research basically focuses on developing diagnostic accuracy as opposed to making it interpretable and deployable in real clinical settings, very critical for adaptation in healthcare setup. Additionally, there exists a gap in integrating imaging data with other genomic, demographic, and biomarker data to achieve more comprehensive cancer diagnosis and risk prediction. Future work should be devoted to developing clinically validated, interpretable, and resource-efficient deep learning models that generalize well across diverse patient populations.

IV. CONCLUSION

Deep learning has emerged as the prime tool in the early detection and diagnosis of women's cancers, having high accuracy and automation in medical imaging, histopathology, and genomic analysis. This review highlights the effectiveness of CNNs, RNNs, transformer-based models, and hybrid techniques to enhance diagnostic precision for cancers in the breast, cervix, ovaries, and uterus. Despite these gains, there is still much work to be done. Data scarcity, model interpretability, and ethical concerns stand in the way of integrating these systems into clinical workflows. Developing clinically robust, explainable, and ethically sound AI-driven solutions requires a cross-disciplinary effort between AI researchers, oncologists, and policymakers. Explaining AI, federated learning, and multi-modal fusion techniques represent promising avenues to improve the reliability of the model and applicability in the real world. While deep learning has the promise to revolutionize oncology, further research and clinical validation will be required before these technologies begin to translate into tangible improvements in cancer detection, patient outcomes, and overall healthcare delivery.

REFERENCES

[1] Kavousi, S., Maharlouei, N., Rezvani, A., Aliabad, H. A., & Vardanjani, H. M. (2024). Worldwide association of the gender inequality with the incidence and mortality of cervical, ovarian, endometrial, and breast cancers. *SSM-Population Health*, *25*, 101613.

[2] Al-Badawi, I. A., Abu-Zaid, A., Alomar, O., Alsabban, M., Alsehaimi, S. O., Alqarni, S. M., ... & Salem, H. (2024). Association between Endometriosis and the Risk of Ovarian, Endometrial, Cervical, and Breast Cancer: A Population-Based

Study from the US National Inpatient Sample 2016–2019. *Current Oncology*, *31*(1), 472-481.

[3] Dhokotera, T. G., Muchengeti, M., Davidović, M., Rohner, E., Olago, V., Egger, M., &Bohlius, J. (2024). Gynaecologic and breast cancers in women living with HIV in South Africa: a record linkage study. *International journal of cancer*, *154*(2), 284-296.

[4] Chen, C., Shi, H., Yang, J., Bao, X., & Sun, Y. (2024). The risk of breast cancer and gynecologic malignancies after ovarian stimulation: meta-analysis of cohort study. *Critical Reviews in Oncology/Hematology*, 104320.

[5] Ng, C. W., Tsang, Y. T., Gershenson, D. M., & Wong, K. K. (2024). The prognostic value of MEK pathway–associated estrogen receptor signaling activity for female cancers. *British journal of cancer*, *130*(11), 1875-1884.

[6] Sarhangi, H. A., Beigifard, D., Farmani, E., &Bolhasani, H. (2024). Deep Learning Techniques for Cervical Cancer Diagnosis based on Pathology and Colposcopy Images. *Informatics in Medicine Unlocked*, 101503.

[7] Devi, S., Gangarde, R., Deokar, S., Muqeemuddin, S. F., Awasthi, S. R., Shekhar, S., ... & Joshi, S. (2024). Public health nurse perspectives on predicting nonattendance for cervical cancer screening through classification, ensemble, and deep learning models. *Public Health Nursing*.

[8] Rai, H. M. (2024). Cancer detection and segmentation using machine learning and deep learning techniques: A review. *Multimedia Tools and Applications*, *83*(9), 27001-27035.

[9] Goyal, M., Tafe, L. J., Feng, J. X., Muller, K. E., Hondelink, L., Bentz, J. L., & Hassanpour, S. (2024). Deep Learning for Grading Endometrial Cancer. *The American Journal of Pathology*.

[10] Garg, P., Sharma, P., & Prakash, U. M. (2024, January). Advancing Breast Cancer Prediction and Early Detection with Advanced Deep Learning Models. In *2024 Fourth International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)* (pp. 1-6). IEEE.

[11] Shiwlani, A., Ahmad, A., Umar, M., Dharejo, N., Tahir, A., &Shiwlani, S. (2024). BI-RADS Category Prediction from Mammography Images and Mammography Radiology Reports Using Deep Learning: A Systematic Review. *JurnalIlmiah Computer Science*, *3*(1), 30-49.

[12] Wang, L. (2024). Mammography with deep learning for breast cancer detection. *Frontiers in Oncology*, *14*, 1281922.

[13] Chegini, M., &Mahlooji Far, A. (2024). Uncertainty-aware deep learning-based CAD system for breast cancer classification using ultrasound and mammography images. *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, *12*(1), 2297983.

[14] Thakur, N., Kumar, P., & Kumar, A. (2024). A systematic review of machine and deep learning techniques for the identification and classification of breast cancer through medical image modalities. *Multimedia Tools and Applications*, *83*(12), 35849-35942.

[15] Wen, X., Guo, X., Wang, S., Lu, Z., & Zhang, Y. (2024). Breast cancer diagnosis: A systematic review. *Biocybernetics and Biomedical Engineering*, *44*(1), 119-148.

[16] Sureshkumar, V., Prasad, R. S. N., Balasubramaniam, S., Jagannathan, D., Daniel, J., & Dhanasekaran, S. (2024). Breast cancer detection and analytics using hybrid CNN and extreme learning machine. *Journal of Personalized Medicine*, *14*(8), 792.

[17] Nafea, A. A., Manar, A. M., Alheeti, K. M. A., Alsumaidaie, M. S. I., & AL-Ani, M. M. (2024). A Hybrid Method of 1D-CNN and Machine Learning Algorithms for Breast Cancer Detection. *Baghdad Sci. J*, *21*, 3333.

[18] Ajlouni, N., Özyavaş, A., Ajlouni, F., Takaoğlu, M., &Takaoğlu, F. (2024). Enhancing TNM Staging in Breast Cancer: A Hybrid Approach with CNN, Edge Detection, and Self-Organizing Maps for Improved Accuracy.

[19] Rani, N. D., & Arrama, M. B. (2024). Detection of Ovarian Cancer with optimized Neural Networks using Convolutional LSTM. *Library Progress International*, *44*(3), 17174-17188.

[20] Rajesh, P., Thanjaivadivel, M., Arulkumaran, G., & Jagannathan, J. (2024). MRI-Enhanced Metastatic Ovarian Tumor Detection: Leveraging Enhanced 3D CNN and Data Augmentation for Exceptional Accuracy.

[21] Behera, S. K., Das, A., & Sethy, P. K. (2024). Deep fine-KNN classification of ovarian cancer subtypes using efficientNet-B0 extracted features: A comprehensive analysis. *Journal of Cancer Research and Clinical Oncology*, *150*(7), 361.

[22] Das, A., Chilakarao, M., Biswas, P., Sethy, P. K., Dalai, M. K., & Behera, S. K. (2024, January). DeepOvaNet: A Comprehensive Deep Learning Framework for Predicting and Diagnosing Ovarian Cancer in Women Across Menopausal Transitions. In *2024 Fourth International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)* (pp. 1-7). IEEE.

[23] Ziyambe, B., Yahya, A., Mushiri, T., Tariq, M. U., Abbas, Q., Babar, M., ... & Jabbar, S. (2023). A deep learning framework for the prediction and diagnosis of ovarian cancer in pre-and post-menopausal women. *Diagnostics*, *13*(10), 1703.

[24] Martinez, R. G., & van Dongen, D. M. (2023). Deep learning algorithms for the early detection of breast cancer: A comparative study with traditional machine learning. *Informatics in Medicine Unlocked*, *41*, 101317.

[25] Youneszade, N., Marjani, M., & Pei, C. P. (2023). Deep learning in cervical cancer diagnosis: architecture, opportunities, and open research challenges. *IEEE Access*, *11*, 6133-6149.

[26] Humayun, M., Khalil, M. I., Almuayqil, S. N., &Jhanjhi, N. Z. (2023). Framework for detecting breast cancer risk presence using deep learning. *Electronics*, *12*(2), 403.

[27] Al Fryan, L. H., Shomo, M. I., & Alazzam, M. B. (2023). Application of Deep Learning System Technology in

Identification of Women's Breast Cancer. *Medicina*, *59*(3), 487.

[28] Xue, P., Wang, J., Qin, D., Yan, H., Qu, Y., Seery, S., ... & Qiao, Y. (2022). Deep learning in image-based breast and cervical cancer detection: a systematic review and meta-analysis. *NPJ digital medicine*, *5*(1), 19.

[29] Allugunti, V. R. (2022). Breast cancer detection based on thermographic images using machine learning and deep learning algorithms. *International Journal of Engineering in Computer Science*, *4*(1), 49-56.

[30] Wang, Y., Acs, B., Robertson, S., Liu, B., Solorzano, L., Wählby, C., ... &Rantalainen, M. (2022). Improved breast cancer histological grading using deep learning. *Annals of Oncology*, *33*(1), 89-98.