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Deep Learning Models for Early Detection of Ovarian Cancer: A Systematic Review of Ultrasound-Based Diagnostic Tools

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Abstract - **Ovarian Cancer (OC) remains one of the most lethal gynecological malignancies, with a global 5-year survival rate of only 45%. This project aimed to assess the potential of deep learning-based diagnostic tools in improving early detection of ovarian cancer, particularly through ultrasound imaging. The primary research problem lies in the challenge of accurately diagnosing OC at an early stage, as traditional imaging techniques often rely on subjective interpretations, leading to inconsistent results. To address this issue, a systematic review was conducted following PRISMA guidelines, evaluating studies published between January 2018 and May 2023 in the Scopus and PubMed databases. These studies employed deep learning or artificial intelligence models for the diagnosis, prognosis, or identification of OC from ultrasound images. Of the 101 studies screened, 9 met the inclusion criteria. The included studies reported diagnostic accuracies of deep learning models ranging from 75% to 100%, with sensitivities between 85% and 99%. The conclusions indicate that deep learning models significantly enhance the diagnostic accuracy of ovarian cancer, offering a promising non-invasive tool for early detection. This research underscores the importance of integrating AI technologies into clinical practice to improve survival outcomes for OC patients.**
Keywords: **Ovarian Cancer (OC), Deep Learning, Early Detection, Ultrasound Imaging, Artificial Intelligence (AI)**

I. INTRODUCTION

Ovarian cancer originates in the ovaries, the female reproductive organs responsible for egg production. This malignancy often presents vague symptoms that can be easily misinterpreted until it progresses to an aggressive stage, deeply rooted within the ovarian tissue [1]. Its elusive early-stage symptoms have earned it the moniker "silent killer." There are three primary classifications of ovarian cancer: epithelial ovarian cancer, stromal tumors, and germ cell tumors [2]. Globally, with a survival rate of less than 45% over five years, ovarian cancer ranks as the seventh most prevalent cancer in women and the eighth leading cause of cancer-related deaths [3]. Epithelial ovarian carcinoma (EOC) accounts for up to 90% of all ovarian cancer cases and is the deadliest. The disease has various cellular origins and is sometimes termed tubo-ovarian cancer due to its potential manifestation as a primary peritoneal malignancy, an ovarian or fallopian tube tumor, or a combination of both [4].

To date, no screening techniques have demonstrated definitive efficacy. Often, the diagnostic process for ovarian cancer begins with the unintended detection of masses during imaging or the palpation of an adnexal tumor during a pelvic examination [1]. The absence of efficient early detection and diagnostic strategies, coupled with the rapid spread of the disease across the peritoneal surface, significantly contributes to the high mortality rate associated with OC [5].

Primary tools for detection, diagnosis, and subsequent monitoring of unexplained ovarian cancer (OC) include imaging modalities such as ultrasound imaging (US), computed tomography (CT), and magnetic resonance imaging (MRI) [6]. Among these, US stands out for its convenience, cost-effectiveness, absence of radiation, and superior resolution in delineating OC. Consequently, ultrasound remains the principal diagnostic tool for ovarian cancer detection and lesion identification. However, challenges such as interobserver variability exist, and image interpretation can be complex [7].

Deep learning is a subset of artificial intelligence that incorporates three or more layers of neural networks. These networks attempt to simulate human brain activity by learning from massive datasets [8]. Deep learning has several applications, including voice-enabled technologies and image recognition. It enables systems to learn complex concepts by building them from simpler ones, resulting in a multilayer hierarchy. Recent advancements in deep learning have showcased remarkable achievements in visual pattern recognition [1].

Incorporating a deep learning component seamlessly within the imaging workflow can augment physician capabilities. Such integration can enhance efficiency, minimize manual interventions, equip radiologists with quantitative features, highlight intricate patterns imperceptible to the human eye, and offer more precise and consistent radiological evaluations than current methodologies. This paves the way for accurate preoperative diagnoses and early ovarian cancer detection [1].

Furthermore, the literature has documented a plethora of computer vision tasks, encompassing segmentation [9], classification [10], and lesion detection [11], based on deep learning, with ultrasound being the primary diagnostic modality under consideration. Employing deep learning techniques on tumor images holds promise not only for aiding image interpretation but also for potential applications in screening and prognosis.

A. Rationale

The motivation behind this research lies in conducting a comprehensive review of prior studies that have explored the application of deep learning diagnostic instruments for the prediction or detection of ovarian cancer using ultrasound imagery combined with clinical data. This review is necessary to assess the diagnostic performance of deep learning-based tools developed for detecting ovarian cancer.

Consequently, the question addressed is: "Are deep learning models efficient diagnostic tools for the detection of ovarian cancer from ultrasound images?" The evaluation will hinge on performance metrics, including, but not limited to, sensitivity, specificity, accuracy, and other pertinent measures.

II. MATERIALS AND METHODS

A. Information Source and Search Strategies

The PubMed and Scopus database libraries were comprehensively searched for studies published between January 1, 2018, and May 5, 2023, that developed a deep learning algorithm for the diagnostic performance of ovarian cancer from ultrasound images.

The search was carried out using the combination of the following keywords:

1. Search terms related to deep learning: "deep learning," "artificial intelligence," "neural network," AI, CNN, or "machine learning";
2. Search terms related to diagnosis: diagnosis, detection, prediction, discovery, or identification;
3. Search terms related to ovarian cancer: ("ovar* cancer," "ovarian neoplasm," or "ovar* carcinoma");
4. Search terms related to ultrasound images: "ultrasound images," "ultrasonography," or "diagnostic images."

B. Eligibility Criteria

1. Inclusion Criteria

a. Studies that include human patients with ovarian cancer.
b. Studies that use deep learning models or artificial intelligence models to predict, detect, or classify ovarian cancer.
c. Studies that utilize ultrasound images.
d. Quantitative studies.
e. Peer-reviewed articles published in the English language.

2. Exclusion Criteria

a. Studies that involve non-human patients.
b. Studies that do not use deep learning models.
c. Studies that utilize other forms of imaging technology.
d. Studies published in languages other than English.
e. Studies published before 2018.
f. Systematic reviews, reviews, editorials, and duplicate publications.

C. Study Selection

The retrieved papers were exported to a CSV file, and duplicates were removed through additional screening. Two reviewers (AOO and KCU) worked separately on the screening and full-text review. Once an agreement was reached, studies were selected. In cases of uncertainty, the selection was reviewed by all three authors (EEO, AOO, and KCU).

D. Data Extraction

Two separate reviewers undertook the data extraction process utilizing a predetermined form. The extracted data encompass study attributes such as author(s) name, year of publication, ultrasound images of the subjects, the specific deep learning model employed, prediction models, and performance metrics of the deep learning tool used. In cases of discrepancies, a third reviewer was consulted to achieve consensus.

E. Quality Assessment

The researchers meticulously assessed the quality of studies by applying eligibility criteria to filter out articles that did not align with the search criteria or address the focal point of the review.

III. RESULTS OF THE STUDY

Upon the initial search, 101 records were identified. Of these, 13 duplicates were eliminated, and 41 studies were dismissed after screening their titles and abstracts. This left 47 studies for a comprehensive full-text review. Out of these, 38 were subsequently excluded for various reasons: addressing a different disease (n = 1), not employing deep learning (n = 26), being a systematic review (n = 3), not using ultrasound (n = 2), and availability of only the abstract without full text (n = 6). Consequently, a total of 9 articles were deemed suitable for inclusion in this review.

To ensure the quality and relevance of the academic literature incorporated into this review, a meticulous evaluation strategy was employed. This encompassed cross-referencing all duplicates with their original sources, conducting an in-depth review of article abstracts, and scrutinizing each article against predetermined inclusion and exclusion criteria. The detailed process is depicted in Fig. 1.

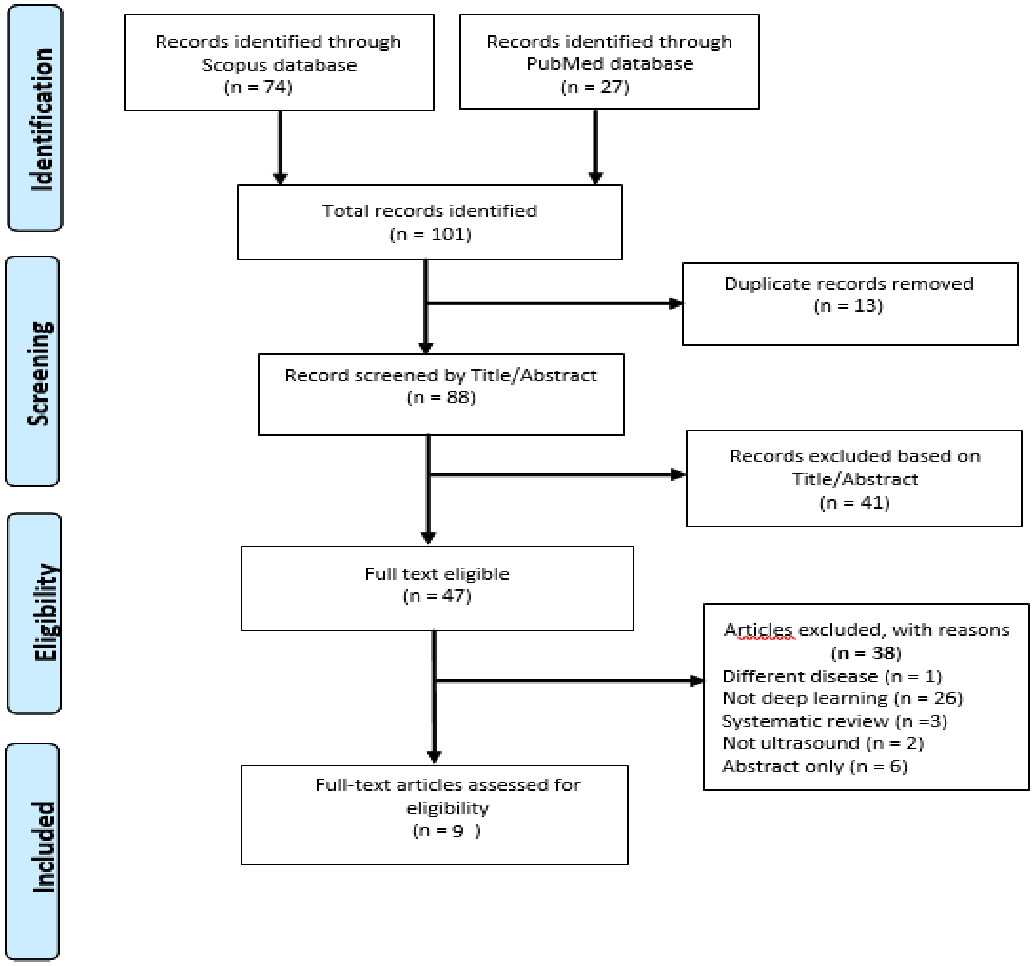

Fig. 1 PRISMA flow diagram illustrating the study selection

A. Study Characteristics

A summary of the characteristics of included studies, which includes 9 studies, published from 2013 till 2023, have been given in Table I below.

TABLE I SUMMARY OF INCLUDED STUDIES

Author(s)	No of Images	Deep Learning Tool	Data Types	Study Aim	Result	Performance Metric	Conclusion
Jung Y, *et al.,* [7]	1613	CNN-CAE	Ultrasound images with pathological diagnosis	To accurately diagnose malignant and various benign ovarian tumors using texture on ultrasound images	Shows promising results in the classification of ovarian tumor	Accuracy: 90.12% Sensitivity: 86.67% AUC: 0.9906	The model shows promise as a feasible diagnostic tool for ovarian tumors
Gao Y, *et al.,* [1]	575930	Deep Convolutional Neural Network (DCNN)	Ultrasound images	To create a DCNN model that automatically evaluates ultrasound images, improving the accuracy of ovarian cancer diagnosis compared to current methods.	DCNN model outperformed radiologists in detecting ovarian cancer, improving accuracy and sensitivity significantly.	Average AUC: 0.870 Accuracy: 87.6% Sensitivity: 82.7%	DCNN-enhanced ultrasound outperformed radiologists and improved their accuracy.

Arezzo F, *et al.,* [4]		Logistic Regression (LR), Random Forest (RFF), and K-Nearest Neighbours (KNN).	Ultrasound images with pathological diagnosis	To develop a tool to predict 12-month Progression-Free survival in patients with OC based on an ML algorithm applied to gynecological ultrasound assessment	RFF showed the best performance	Accuracy 93.7%, Precision 90%, Recall 90% AUROC 0.92)	An accurate ML model to predict 12-month PFS was developed
Hsu ST, *et al.,* [12]	1896	Convolutional Neural Network (CNN)	Ultrasound images	To develop a system that automates the characterization of ultrasound images of ovarian tumors	The ensemble classifier method outperformed the single classifiers in terms of accuracy, sensitivity, and specificity	Accuracy: 92.15% Sensitivity: 91.37% Specificity: 92.92%	The proposed method outperformed the methods used in previous studies
Christiansen F, *et al.,* [13]	3077	Deep Neural Networks (DNNs)	Ultrasound images	To develop and test DNN-based ultrasound image analysis to distinguish benign from malignant ovarian tumors and compared it with expert subjective assessment.		The Ovry-Dx2 model achieved a sensitivity of 97.1% and a specificity of 93.7%, with 12.7% of lesions labeled as inconclusive.	Deep neural networks analyzing ultrasound images can predict ovarian malignancy with diagnostic accuracy similar to that of human expert examiners
Chiappa V, *et al.,* [14]	274	Decision Support System (DSS)	Transvaginal ultrasound	To evaluate the performance of a decision support system (DSS) based on radiomics and machine learning in predicting the risk of malignancy of ovarian masses (OMs) from transvaginal ultrasonography (TUS) and serum CA-125.	Decision Support System (DSS) holds promise for predicting malignancy risk in women diagnosed with ovarian masses from transvaginal ultrasound (TUS), aiding clinical decisions.”	Accuracy: 88% sensitivity: 99% specificity: 77%	Decision Support System (DSS) accurately predicts the malignancy risk level of ovarian masses by combining transvaginal ultrasound (TUS) features with clinical and biological parameters.
Wang H *et al.,* [15]	279	DCNN	pathology-confirmed SOTs Ultrasound images	To assess the effectiveness of a deep convolutional neural network (DCNN) in distinguishing between benign, borderline, and malignant serous ovarian tumors (SOTs) using ultrasound (US) images.”	The model could accurately classify benign, malignant, and bother line serous ovarian tumors from ultrasound images	Accuracy: 75% sensitivity: 89%	DCNN model analysis of US images can provide complementary clinical diagnostic information and is thus a promising technique for effective differentiation of benign, borderline, and malignant SOTs.

Martínez-Más J, *et al.,* [16]	348	KNN, SVM, ELM	Ultrasound images	To evaluate different well-known Machine Learning (ML) systems to perform the automatic categorization of ovarian tumors from ultrasound images	Our findings indicate that the KNN classifier yields inaccurate predictions regardless of local approximation size compared to SVM, ELM and LDS.	Accuracy of KNN: 60% Accuracy of other ML: 85%	ML methods can be efficiently used for developing the classification stage in computer-aided diagnosis systems of ovarian tumor from ultrasound images
Rajendra Acharya U, *et al.,* [17]	2600	K-Nearest Neighbour (KNN)/ Probabilistic Neural Networks (PNN)	Ultrasound images	Proposed GynaeScan, an effective CAD technique for detecting ovarian tumors in ultrasound images.		Accuracy: 100% Sensitivity: 100% Specificity: 100%	The suggested technique may serve as an unbiased supplementary approach for identifying the presence or absence of ovarian tumors.

Abbreviations: Convolutional Neural Network Model with a Convolutional Autoencoder (CNN-CAE), Deep Convolutional Neural Network (DCNN), Deep Neural Network (DNN), Machine Learning (ML), Decision Support System (DSS), Computer Aided Diagnostic (CAD), Probabilistic Neural Networks (PNN), Progression-Free Survival (PFS), Support Vector Machine (SVM), Decision Tree (DT), K-Nearest Neighbour (KNN), Naïve Bayes (NB), Extreme Learning Machine (ELM), Linear Discriminant (LD), Random Forest (RFF).

Based on the analysis of the 9 studies that satisfied the inclusion criteria, it was observed that the various deep learning models employed for the classification, prediction, or identification of ovarian tumors from ultrasound images demonstrated accuracies ranging from 75% to 100%. Sensitivities spanned from 85% to 99%, while specificities varied from 74% to 100%. These results surpassed the general subjective evaluations made by seasoned radiologists and sonographers. Such findings underscore the potential of deep learning models as effective diagnostic instruments for detecting ovarian cancer from ultrasound images, thereby augmenting the diagnostic capabilities of radiologists and sonographers and increasing survival outcomes.

IV. DISCUSSION OF THE STUDY

Recent years have witnessed a significant surge in the exploration of deep learning and AI models for cancer diagnosis, including ovarian cancer. This trend is largely driven by the growing application of AI in medical imaging. The diagnostic performance of AI in ovarian cancer utilizing ultrasound imaging is examined in this systematic review. AI has the potential to anticipate preoperative diagnoses, enhance patient triage, and reduce unnecessary procedures. This systematic review investigated the effectiveness of deep learning methodologies in diagnosing ovarian cancer using ultrasound images. The reviewed studies employed various AI and deep learning techniques, including Decision Support Systems, Deep Neural Networks, Convolutional Neural Networks, Random Forests, k-Nearest Neighbors, Linear Discriminants, Support Vector Machines, and Extreme Learning Machines.

A meta-analysis and systematic review of image-based ovarian cancer diagnosis were published by Xu et al. [18]. This review included 17 ultrasound articles with pooled sensitivity and specificity rates of 91% and 87%, respectively. The pooled rates included in the current review are smaller; this may be because our review included a total of 9 papers, and one of the studies from the previously published systematic review has since been retracted. In addition, the findings of the present review may be conservative compared to previous studies, as limited database access may have resulted in a less comprehensive inclusion of relevant studies, underscoring the importance of future research with broader database coverage.

DCNN models automatically evaluate ultrasound images, improving the accuracy of ovarian cancer diagnosis with an average AUC of 0.870, an accuracy of 87.6%, and a sensitivity of 82.7% [1]. CNN models displayed better performance in characterizing ultrasound images of ovarian tumors, with an accuracy of 92.15%, sensitivity of 91.37%, and specificity of 92.92% [12]. Decision Support Systems accurately predict the malignancy risk level of ovarian masses by combining transvaginal ultrasound (TUS) features with clinical and biological parameters, showing an accuracy of 88%, sensitivity of 99%, and specificity of 77% [14].

Using k-Nearest Neighbors and Probabilistic Neural Network classifiers, Acharya *et al.,* [17] utilized 2,600 3D ultrasound images (1,300 benign, 1,300 malignant) with 11 extracted features to achieve 100% classification accuracy in detecting ovarian cancers, as demonstrated in their Gynaescan system.

The evidence from this review indicates that deep learning can be a valuable adjunct to clinicians in determining the origin of ovarian tumors using ultrasound imaging. Furthermore, deep learning models exhibit diagnostic accuracy that matches or even surpasses that of expert clinicians and traditional models [19].

However, the accuracy of these models depends on several factors. The choice of deep learning model is crucial, with some models, such as k-Nearest Neighbors, performing lower than others like Linear Discriminants, Support Vector Machines, and Extreme Learning Machines. Additionally, the quality and quantity of the pathological dataset significantly impact predictive performance. A comprehensive dataset with minimal noise, missing values, and robust clinical parameters can substantially enhance the accuracy of deep learning models in diagnosing ovarian cancer.

A. Limitations

The present study faced significant limitations, primarily due to gaps in existing research. A notable limitation was the scarcity of studies focusing on ultrasound imaging in the application of deep learning for ovarian cancer detection, diagnosis, and prognosis. Despite the abundance of research utilizing magnetic resonance imaging (MRI) and computed tomography (CT), the lack of ultrasound-specific studies constrained the breadth and depth of this review.

Furthermore, another limitation emerged from the oversight of many studies in evaluating the practical applicability and utility of deep learning-based diagnostic tools. Specifically, factors such as cost-effectiveness, user satisfaction, and patient outcomes were often neglected. This omission restricts a comprehensive assessment of deep learning's potential in real-world healthcare settings, underscoring the need for future research to address these critical aspects.

These limitations highlight areas for future research to enhance the understanding and application of deep learning in ovarian cancer diagnosis using ultrasound imaging and to ensure the development of practical and effective diagnostic tools.

V. CONCLUSION

Deep learning techniques have shown impressive accuracy, sensitivity, and specificity in detecting and classifying ovarian cancers from ultrasound images. However, due to the limited number of studies included in this systematic review, drawing definitive conclusions about the effectiveness of deep learning-based diagnostic tools for ovarian cancer detection remains challenging. Future research should focus on rigorous methodologies, larger sample sizes, and standardized evaluation metrics to establish conclusive evidence regarding their effectiveness. It is crucial to evaluate the effectiveness and feasibility of deep learning-based diagnostic tools by considering factors such as cost-effectiveness, user satisfaction, and patient outcomes.

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