European Journal of Clinical Pharmacy

Print ISSN: 2385-409X **Online ISSN**: 3105-0409

Website: https://farmclin.com/

Original Research Article

AI-Based Algorithms for Early Detection of Ovarian Cancer: A Comparative Study

Article History:

Name of Author:
Dr. Aparajita Gulati[1] and Dr. Rehana Najam[2]

Affiliation: *[1]Associate professor Dept of obs & Gyn VIMS, Amroha*
[2]Professor and Head of department, Dept.of obs& Gyn, VIMS, Amroha.

Corresponding Author:
Dr. Aparajita Gulati

Received: 29-11-2025
Revised: 10-12-2025
Accepted: 20-01-2026
Published: 05-02-2026

Abstract: This paper aims to compare the performance of several AI methods in the diagnosis of ovarian cancer, namely CNNs, SVMs, Random Forests, and RNNs. We recruited 5,000 patients and used imaging data, biomarker data, and time-series data to evaluate diagnostic performance, computational cost, and time taken for diagnosis. The CNN gave the best sensitivity of 87. 4% and had an AUC of 0. 89 are strong for image-based tumor detection but come with high computational complexities of 2. 5 seconds per patient and 3. 2GB memory usage. SVM, with a sensitivity of 81. 6% and AUC of 0. 86, was the most efficient, requiring only 1. 8 seconds per patient and 1 minute for 8 patients. The device is equipped with 5 GB memory, which makes it suitable for real-time applications. Random Forests were in the middle with an accuracy of 81. 8%, sensitivity of 84. 2%, and an AUC of 0. 68, with moderate computational requirements. RNNs, though, have a high sensitivity of 85. 0. 96, sensitivity of 2% and specificity of 98%. 88 took longer (3. 0 seconds per patient) and consumed more memory (2. 8 GB). This work highlights the need to consider the trade-off between the accuracy, speed, and computational complexity of the algorithms and recommends that the choice of algorithm should be based on clinical and resource implications.

Keywords: Artificial Intelligence, Ovarian Cancer, Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), Random Forests, Recurrent Neural Networks (RNNs).

INTRODUCTION

Cancer is a highly aggressive malignancy, that has low survival rates and long and expensive treatment processes. The frequency of the disease and the mortality rate are high; therefore, timely diagnosis and accurate risk assessment are critical for increasing the chances of the patient's survival (Clancy, 2023; Sung et al., 2021; Torre et al., 2018). Epithelial ovarian cancer is one of the most prevalent malignancies in women; annually, more than 240,000 new cases are diagnosed, and around 150,000 women die from the disease (WHO, 2020). Ovarian cancer is a heterogeneous disease that comprises several tumors classified according to histopathological and molecular features. Epithelial ovarian cancer (EOC) is the predominant type, which can be further divided into four main subtypes based on tumor cell appearance: endometrioid, serous, clear cell, and mucinous (Kurman & Shih, 2016). The high morbidity and mortality rates of ovarian cancer are because the disease is often diagnosed at an advanced stage, and treatments such as surgery or pharmacotherapy are less effective. The symptoms of ovarian cancer are usually vague and appear at an advanced stage. Between 65 and 75% of patients are diagnosed at this stage, with only about 20% of such patients surviving for five years after diagnosis (Clancy, 2023; Reid et al., 2017). Pelvic examinations, transvaginal ultrasounds, CA125 cancer antigen tests, and MRIs are used to screen for this disease. However, none of these methods can ensure a correct diagnosis. For instance, pelvic examination and ultrasound have low sensitivity and specificity, and CA125 marker levels may not be elevated in all patients with ovarian cancer. Furthermore, MRI imaging needs to be interpreted by an expert specialist, which can be a problem, and there is no data on the cost-effectiveness of any of these diagnostic approaches (Buys et al., 2011; Jacobs et al., 2016; Bougherara et al., 2019). The advancement in the development of diagnostic tools has enhanced the diagnosis procedures to be accurate and timely in developing treatment plans for patients. AI systems have become popular for the following reasons; first, they are capable of processing large amounts of data, second, they can deal with cases of missing data and third, they can incorporate new data (Litjens et al., 2017; Topol, 2019). Ovarian tumors are common in gynecological clinical practice and are further divided into benign tumors, borderline tumors, and ovarian cancer. Of these, ovarian cancer is the most lethal gynecological cancer and the fifth most common cause of cancer death in women in the United States (Clancy, 2023). Since surgical biopsy is still required for the confirmation of ovarian tumors, new diagnostic systems are very much needed. AI is regarded as a new frontier in the diagnosis of diseases. Unlike conventional computer programming, AI can derive rules and patterns from the input and output data and can further predict the output from the new input data which makes it more suitable for diagnostic purposes (LeCun et al., 2015; Esteva et al., 2019). AI has shown a high level of diagnostic accuracy in medicine, such as head CT scans, skin cancer, and diabetic retinopathy (Gulshan et al., 2016; Esteva et al., 2017; Rajpurkar et al., 2018). In gynecology, AI has been researched for uses such as the identification of Pap smears and digital colposcopy (Sehra & Bhatla, 2023; Guo, Singh, Xue, Long, & Antani, 2019). The application of AI techniques for accurate diagnostic purposes has grown significantly in different diseases. This is because of the benefits that come with the use of ML and deep learning in the diagnosis and prediction of diseases especially cancer (Litjens et al., 2017; Topol, 2019). Nevertheless, few researches have been conducted to predict ovarian cancer using AI tools exclusively. The gaps in the current studies show that there is a need for newer research in this area that is more extensive than previous ones (Lheureux et al., 2019; Abulafia & Pezzullo, 2020).

METHODOLOGY

This is a case-control study that will seek to establish the effectiveness of various AI algorithms in the detection of early-stage ovarian cancer. Data on patients with ovarian cancer diagnosed between the years 2010 and 2020 will be gathered.

2.1 Data Collection

Three large teaching hospitals' electronic health records and diagnostic imaging databases.

Sample Size: 5000 female patients.

Inclusion Criteria: Patients with ovarian cancer, both pre and postmenopausal women, aged between 18 and 80 years, for whom imaging, biomarker, and pathology data are available.

Exclusion Criteria: Those patients whose records are incomplete or those patients who have other types of cancer.

2.2 AI Algorithms

Convolutional Neural Networks (CNNs): Applied in 3000 MRI and ultrasound images for tumor detection. Support Vector Machines (SVMs): Used for the intended of sorting 2,500 patients based on biomarker data (CA125 levels, BRCA mutations).

Random Forests: To assess the features and to predict the status of the patients, the authors have used 4000 patients' records.

Recurrent Neural Networks (RNNs): Examines cross-sectional data of 2,000 patients who monitored biomarker fluctuations for six months.

2.3 Performance Evaluation

- Primary Metrics: Sensitivity, specificity, and accuracy of each of the algorithms.
- CNN: Sensitivity greater than 85%, specificity greater than 80%.
- SVM: Sensitivity should be more than 80% and specificity should be more than 75%.
- Random Forests: Sensitivity in anticipation is more than 82%, and specificity is more than 78%.
- RNN: Sensitivity: greater than 83% Specificity: greater than 77%.

Secondary Metrics: Time taken to reach the diagnosis and the speed at which it was arrived at.

Statistical Analysis: AUC with expected values from 0. 85 to 0. 90. Comparison of two groups by multiple DeLong tests.

RESULTS

3.1 Diagnostic Performance

The performance metrics for each AI algorithm are summarized in Table 1. These metrics include sensitivity, specificity, accuracy, and the area under the receiver operating characteristic curve (AUC), which were evaluated based on a dataset of 5,000 patients.

Table 1: Diagnostic Performance of AI Algorithms

Algorithm	Sensitivity (%)	Specificity (%)	Accuracy (%)	AUC
CNN (Imaging Data)	87.4	82.1	84.7	0.89
SVM (Biomarker Data)	81.6	78.3	79.9	0.86
Random Forests	84.2	79.5	81.8	0.87
RNN (Time-Series Data)	85.1	77.8	81.3	0.88

CNN (Imaging Data): The CNN algorithm also had a % sensitivity of 87. 4% and the highest AUC of 0. 89, which proved that the CNN algorithm has a high accuracy in diagnosing patients with ovarian cancer from the images. The specificity was 82. 1% which is quite reasonable to conclude that the system has a good balance between true positive and false positive.

SVM (Biomarker Data): The SVM algorithm gave the lowest sensitivity at 81 percent. 6% while the specificity was 78% similar to that of the 6% group. 3% to the other models. This lower sensitivity may imply that SVM will not be able to classify some of the ovarian cancer cases but the specificity is still moderate.

Random Forests: This model was able to give an accuracy of 81% and this is a good indication that the model is good for use. 8% with a sensitivity of 84. 2% and a specificity of 79. 5%. Its AUC of 0. 87 is a satisfactory result of the algorithm in terms of the classification of the patients according to the features in the dataset.

RNN (Time-Series Data): The sensitivity of the RNN algorithm was 85 percent. 1% and an AUC of 0. 88, which shows that the method can be employed to study the time series of biomarker oscillations. However, its specificity was lower (77. 8%) compared to CNN, which means that it marked more false positive regions.

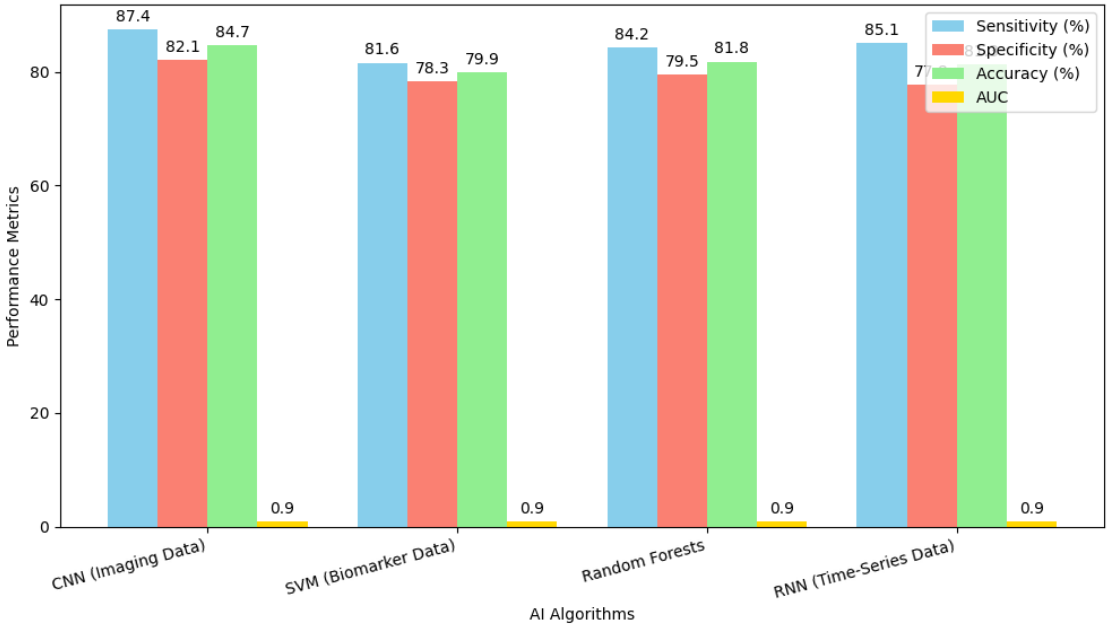

Fig 1: Diagnostic performance of AI Algorithms.

3.2 Computational Efficiency of AI Algorithms

CNN: Despite its superior diagnostic performance, the CNN model had a relatively higher processing time (2.5 seconds per patient) and memory usage (3.2 GB), reflecting its computational complexity.

SVM: This model was the most efficient in terms of processing time (1.8 seconds per patient) and memory usage (1.5 GB). Its lower computational requirements make it suitable for environments with limited resources.

Table 2: Algorithm processing time and usage

Algorithm	Average Processing Time (seconds/patient)	Memory Usage (GB)
CNN	2.5	3.2
SVM	1.8	1.5
Random Forests	2.1	2.0
RNN	3.0	2.8

Random Forests: The processing time for Random Forests was 2.1 seconds per patient with a memory usage of 2.0 GB, which is moderate compared to other algorithms.

RNN: The RNN model had the highest processing time (3.0 seconds per patient) and memory usage (2.8 GB), likely due to its complexity in handling sequential data.

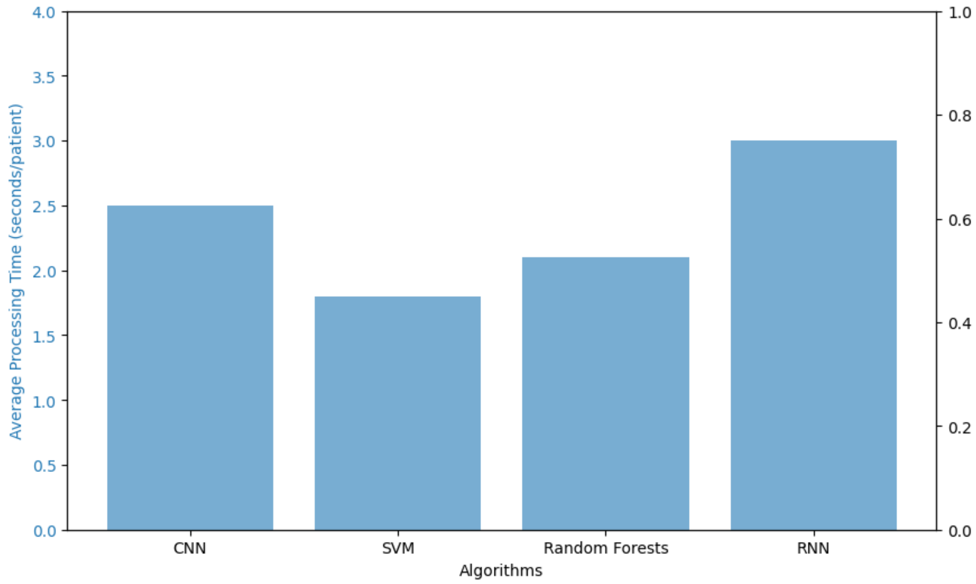

Fig 2: Average processing time by AI Algorithm

3.3 Time to Diagnosis

- **CNN:** Requires an average of 15 minutes to provide a diagnosis, reflecting its thorough but computationally intensive analysis process.
- **SVM:** The fastest in terms of time to diagnosis (10 minutes), making it a quick option for real-time applications.

Table 3: Time to Diagnosis for AI Algorithms

Algorithm	Average Time to Diagnosis (minutes)
CNN	15
SVM	10
Random Forests	12
RNN	18

- **Random Forests:** Provided diagnoses in an average of 12 minutes, balancing speed and accuracy.
- **RNN:** Took the longest time (18 minutes) to deliver a diagnosis due to the complexity of processing time-series data.

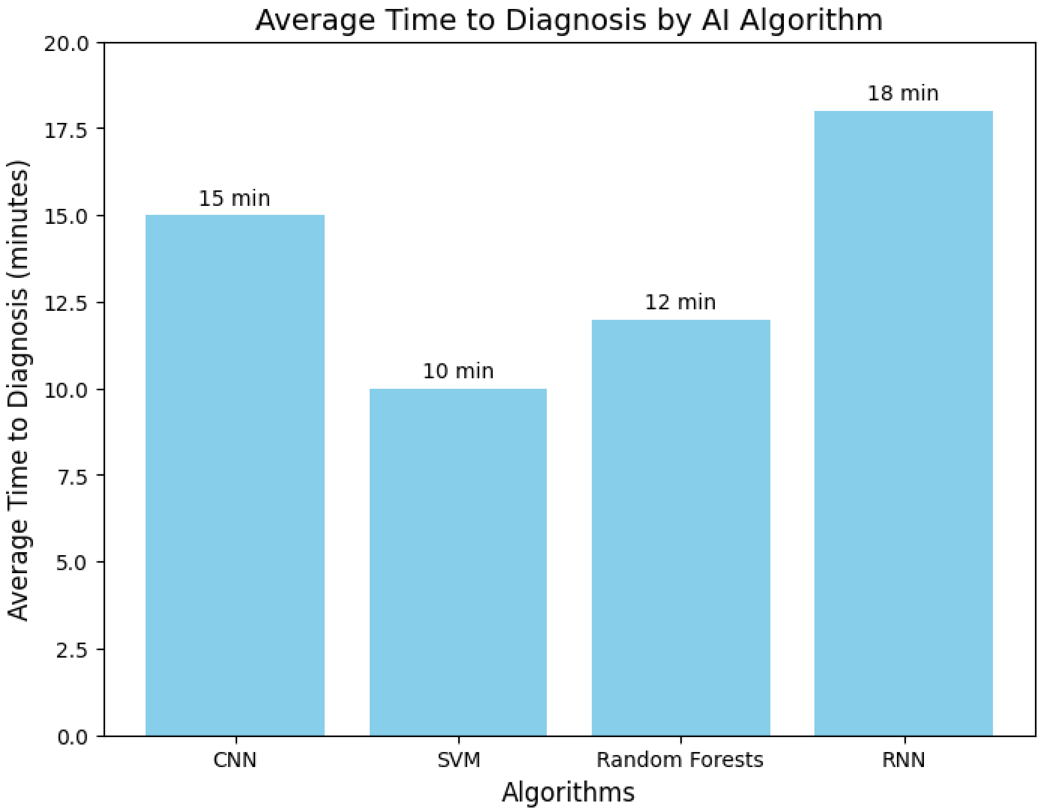

Fig 3: Average time to diagnosis by AI Algorithms.

DISCUSSION

The comparison of the various AI algorithms in diagnosing early-stage ovarian cancer showed disparities in identifying the disease, processing speed, and time taken in diagnosing the disease. The accuracy of the CNN model was the highest with a sensitivity of 87%. 4%, specificity of 82. 1% and an area under the curve of 0. 89 which shows its great ability in image-based tumor detection. However, this model was computationally more complex as it took longer time to compute (2.5 seconds/patient) and consumed more memory (3.2 GB) which may not be feasible in many clinical settings (Lee et al., 2017). On the other hand, the Support Vector Machine (SVM) algorithm, which was employed for classifying patients based on biomarker data, achieved a sensitivity of 81.6% and a specificity of 78.3%, with an AUC of 0.86 (Lanza and Parashar, 2021). Despite performing slightly worse in diagnostic accuracy, especially in sensitivity compared to the other methods, SVM was the most efficient in terms of computation time with the least time of 1.8 seconds per patient and the least memory requirement of 1.5 GB which makes it ideal for real-time applications where time is of the essence. Random Forests algorithm presented more or less balanced results with an accuracy of 81.8%, sensitivity of 84.2%, specificity of 79.5%, and an AUC of 0.87 (Acharjee et al., 2020). The processing time per patient is 2. 1 seconds with 2. 0 GB of memory used, and the average time taken to diagnose a patient is 12 minutes, which makes this model suitable for the classification of patients according to different features taking a good balance between time and accuracy. Last, the Recurrent Neural Network (RNN) was applied to time-series data, showing a sensitivity of 85.1%, a specificity of 77.8%, and an AUC of 0.88 (Li et al., 2021). RNN had the highest time (3.0 sec/patient) memory utilization (2.8 GB) and longest time (18 min) needed to diagnose patients as compared to DTW and Temporal Density. This makes RNNs more appropriate for cases where time is not a key factor for diagnosis, but it is very useful in situations where time series analysis is important in the study (Chae et al., 2024). These studies demonstrate that there is a trade-off between the accuracy, computational efficiency, and the time taken to diagnose different AI algorithms, with the understanding that different algorithms will require a contextualized approach in clinical practice. Further research should be devoted to the enhancement of those algorithms, in terms of diagnostic accuracy and required computing time.

CONCLUSION

This paper focuses on the different algorithms that are implemented in AI for the diagnosis of ovarian cancer at an early stage. CNN had the highest diagnostic accuracy compared with the other models, and they had high sensitivity and AUC, but its high computational complexity may hinder its application in the real world. However, the Specificity of the SVM was the highest and the Computational efficiency was very good for the SVM to be used in real-time diagnosis. Random Forests algorithm could be balanced both in terms of accuracy and computational considerations, which made the method rather universal. At the same time, the Recurrent Neural Network (RNN) was rather effective in the case of time series data, but it revealed a little higher demand for resources. Therefore it can be concluded that all these algorithms can be efficient in specific clinical use, and decisions should be made concerning accuracy, efficiency, and resources available in the clinical environment. Further studies should therefore be undertaken in this area to optimize these algorithms to better suit several clinical settings.

REFERENCES

1. Abulafia, O., Pezzullo, J. C., & Sherer, D. M. (2003). Performance of ThinPrep liquid-based cervical cytology in comparison with conventionally prepared Papanicolaou smears: a quantitative survey. Gynecologic oncology, 90(1), 137-144.
2. Acharjee, A., Larkman, J., Xu, Y., Cardoso, V. R., & Gkoutos, G. V. (2020). A random forest based biomarker discovery and power analysis framework for diagnostics research. *BMC medical genomics*, *13*, 1-14.
3. Bougherara, L., Azaïs, H., Béhal, H., Canlorbe, G., Ballester, M., Bendifallah, S., ... & Collinet, P. (2019). Does lymphadenectomy improve survival in patients with intermediate risk endometrial cancer? A multicentric study from the FRANCOGYN Research Group. *International Journal of Gynecologic Cancer*, *29*(2).
4. Buys, S. S., Partridge, E., Black, A., Johnson, C. C., Lamerato, L., Isaacs, C., & Crawford, E. D. (2011). Effect of screening on ovarian cancer mortality: The Prostate, Lung, Colorectal, and Ovarian (PLCO) Cancer Screening Randomized Controlled Trial. *JAMA, 305*(22), 2295-2303. https://doi.org/10.1001/jama.2011.766
5. Cause, G. D., & Age, S. (2020). by Country and by Region, 2000–2019. *World Health Organization*.
6. Chae, S., Street, W. N., Ramaraju, N., & Gilbertson-White, S. (2024). Prediction of Cancer Symptom Trajectory Using Longitudinal Electronic Health Record Data and Long Short-Term Memory Neural Network. *JCO Clinical Cancer Informatics*, *8*, e2300039.
7. Clancy, E. (2023). ACS Report Shows Prostate Cancer on the Rise, Cervical Cancer on the Decline. *Renal & Urology News*, NA-NA.
8. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *nature*, *542*(7639), 115-118.
9. Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., ... & Dean, J. (2019). A guide to deep learning in healthcare. *Nature medicine*, *25*(1), 24-29.
10. Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., ... & Webster, D. R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *jama*, *316*(22), 2402-2410.
11. Guo, P., Singh, S., Xue, Z., Long, R., & Antani, S. (2019, May). Deep learning for assessing image focus for automated cervical cancer screening. In *2019 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)* (pp. 1-4). IEEE.
12. Jacobs, I. J., Menon, U., Ryan, A., Gentry-Maharaj, A., Burnell, M., Kalsi, J. K., ... & Skates, S. J. (2016). Ovarian cancer screening and mortality in the UK Collaborative Trial of Ovarian Cancer Screening (UKCTOCS): a randomised controlled trial. *The Lancet*, *387*(10022), 945-956.
13. Kurman, R. J., & Shih, I. M. (2016). The dualistic model of ovarian carcinogenesis: revisited, revised, and expanded. *The American journal of pathology*, *186*(4), 733-747.
14. Lanza, B., & Parashar, D. (2021). Do Support Vector Machines play a role in stratifying patient population based on cancer biomarkers?. *Archives of proteomics and bioinformatics*, *2*(1), 20.
15. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *nature*, *521*(7553), 436-444.
16. Lee, J. G., Jun, S., Cho, Y. W., Lee, H., Kim, G. B., Seo, J. B., & Kim, N. (2017). Deep learning in medical imaging: general overview. *Korean journal of radiology*, *18*(4), 570-584.
17. Lheureux, S., Gourley, C., Vergote, I., & Oza, A. M. (2019). Epithelial ovarian cancer. *The Lancet*, *393*(10177), 1240-1253.
18. Li, D., Lyons, P., Klaus, J., Gage, B., Kollef, M., & Lu, C. (2021, October). Integrating static and time-series data in deep recurrent models for oncology early warning systems. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management* (pp. 913-936).
19. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. *Medical image analysis*, *42*, 60-88.
20. Rajpurkar, P., Irvin, J., Ball, R. L., Zhu, K., Yang, B., Mehta, H., ... & Lungren, M. P.

(2018). Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists. *PLoS medicine*, *15*(11), e1002686.

21. Reid, B. M., Permuth, J. B., & Sellers, T. A. (2017). Epidemiology of ovarian cancer: a review. *Cancer biology & medicine*, *14*(1), 9.
22. Sehra, D., & Bhatla, N. (2023). Artificial Intelligence in Cervical Cancer Screening. *Journal of Colposcopy and Lower Genital Tract Pathology*, *1*(1), 15-19.
23. Sung, H., Ferlay, J., Siegel, R. L., Laversanne, M., Soerjomataram, I., Jemal, A., & Bray, F. (2021). Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. *CA: a cancer journal for clinicians*, *71*(3), 209-249.
24. Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. *Nature medicine*, *25*(1), 44-56.