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CASE STUDY

Advancing Ovarian Cancer Diagnosis Using Pre-Trained AI Models and Machine Learning

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ABSTRACT

Ovarian cancer continues to be one of the most lethal cancers affecting the female reproductive system due to late-stage diagnosis and limited effective screening methods. Traditional diagnostic methods for ovarian cancer typically rely on imaging, histopathological analysis, and biomarker detection, which can be slow and prone to human error. Recent developments in the areas of Artificial Intelligence (AI) & Machine Learning (ML) collectively have demonstrated significant role in improving precision as well as efficiency while detecting and classifying ovarian cancer. The study in this paper explores the role of AI models that have been pre-trained, particularly deep learning architectures, to analyze various types of medical data, including histopathological images, radiological scans, and genomic information. By utilizing transfer learning, these models can efficiently extract important features from large datasets and adapt them for ovarian cancer classification with minimal computational demands. The suggested framework integrates Convolutional Neural Networks (CNNs) for analyzing images with conventional machine learning techniques to process genomic and clinical data. Experimental findings show that pre-trained models significantly boost diagnostic accuracy, offering improved sensitivity and specificity over traditional approaches. Furthermore, methods like Grad-CAM have been employed so that it can increase the model's transparency, aiding its acceptance in clinical settings. This study highlights the promise of AI-driven diagnostic tools in supporting detection of the disease early & tailored treatment for ovarian cancer. Findings of this paper highlight importance of integrating deep learning with specialized domain knowledge to improve diagnostic precision while reducing false positives and negatives. Future research will focus on expanding datasets, enhancing model generalization, and investigating real-time clinical implementation. Overall, the study demonstrates that well-adapted pre-trained AI models can transform ovarian cancer diagnosis, offering faster, more accurate, and cost-efficient healthcare solutions.

Keywords: Ovarian cancer, Artificial Intelligence, Machine Learning, Pre-trained models, Deep learning, Medical imaging, Diagnosis, Transfer learning.

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Background of the study

Ovarian cancer is among most fatal cancers related to women health, primarily due to lack of adequate noticeable symptoms in the early stages. So, it is frequently detected in a later stage when treatment choices are limited, contributing to its high mortality rate. The traditional diagnostic process involves a combination of imaging techniques, biomarker testing, and histopathological evaluation. Nonetheless, these approaches often face challenges, including subjectivity, inconsistency in interpretation, and delayed detection. Recent developments in Artificial Intelligence (AI) & Machine Learning (ML) have revealed new approaches which can significantly enhance the accuracy, efficiency, and speed of diagnosing ovarian cancer[1].

Models of Machine Learning, primarily deep learning models, promise significant success in analyzing medical images, recognizing patterns, and performing predictive analysis. The capability of AI systems in handling huge amounts of data of medical records and in revealing underlying patterns makes them valuable for the detection of the disease early and classification of cancer. Particularly, pre-trained deep learning models are able to gain considerable attention for their capability to leverage features learned from large datasets and apply them to specific medical tasks, all while reducing computational demands. This approach, known as transfer learning, enables AI models to adapt to ovarian cancer detection using relatively small datasets while maintaining high accuracy and reliability[2].

Obstacles in Diagnosing Ovarian Cancer

Diagnosing ovarian cancer is challenging because early-stage symptoms are often unclear, and it largely depends on imaging techniques viz. ultrasound, computed tomography (CT), and magnetic resonance imaging (MRI). While these methods provide important diagnostic information, their analysis heavily relies on the expertise of the radiologists and the pathologists, which can lead to variations in results. In addition, serum biomarkers such as CA-125 are commonly used for detection, but they often lack specificity, as increased levels can also occur in non-cancerous conditions.

Histopathological analysis remains the gold standard for confirming a diagnosis, but the manual inspection of tissue samples is labor-intensive and prone to human error. Furthermore, variability between observers can result in inconsistencies in classification, which can influence treatment choices. These challenges highlight the increasing demand for automated, AI-driven diagnostic tools that can deliver precise, reliable, and prompt results[3].

Role of Pre-Trained AI Models in Medical Diagnosis

Pre-trained AI models, e.g. convolutional neural networks (CNNs) which have revealed exceptional effectiveness in image-based medical diagnostics. These models firstly have been trained on extensive datasets of general images, then fine-tuned with specialized medical data to improve their accuracy. By leveraging features learned from diverse image datasets, pre-trained models can efficiently identify patterns and abnormalities in ovarian cancer detection with minimal training data requirements. In addition to CNNs, other machine learning techniques like Random Forests, Support Vector Machines (SVM), & deep neural networks have also been employed to do analysis of clinical as well as genomic data. By combining these AI techniques with radiological images, histopathological slides, and biomarker data, a more comprehensive diagnostic framework is created, improving classification accuracy while minimizing occurrence of false positives as well as false negatives[4].

Benefits of AI in Detecting Ovarian Cancer

Incorporating AI into detection of the ovarian cancer provides the following benefits:

- ☐ ***Early Detection:*** AI models are able to identify subtle patterns in imaging as well as genomic data which can be overlooked in manual assessments, leading to earlier detection of malignancies.
- ☐ ***Improved Accuracy:*** AI-driven analysis reduces inter-observer variability, ensuring consistent and precise diagnosis.
- ☐ ***Time Efficiency:*** Automated processing of medical images and clinical data significantly reduces diagnostic time, enabling faster decision-making for treatment.
- ☐ ***Tailored Treatment:*** AI models have the ability to assess patient-specific data to forecast tumor progression and suggest personalized treatment strategies.
- ☐ ***Cost-Effective Solutions:*** AI-assisted diagnostics can potentially lower healthcare costs by minimizing the need for multiple tests and reducing diagnostic errors[5].

While AI and ML have shown considerable promise in diagnosing ovarian cancer, further research work will be required so that improvements can be done in the consistency, usability of these models in various environments. Expanding datasets, incorporating multi-modal data fusion, and enhancing model interpretability are critical steps toward clinical implementation. Additionally, cooperation between AI researchers, oncologists, and radiologists will be crucial for creating dependable and ethically responsible AI-driven diagnostic tools[6].

The study of this paper aims to expand the potential of pre-trained AI models at improving the detection and classification related to ovarian cancer. By incorporating the techniques of deep learning with multi-modal medical data, the research seeks to advance the current diagnostic landscape and pave the way for AI-powered healthcare solutions.

LITERATURE REVIEW

Ovarian cancer is quite a challenging type of cancer to detect at an early stage, largely due to the absence of symptoms in its initial phases, contributing to its high mortality rate. Recently, there has been a significant growth in the application of Artificial Intelligence (AI) in medical diagnostics, particularly within oncology. Several studies have explored AI-driven approaches for improving ovarian cancer detection, classification, and prognosis prediction. This literature review discusses existing research on AI and ML applications in ovarian cancer diagnosis, with a specific focus on pre-trained models, deep learning architectures, and multi-modal data integration.

Role of Machine Learning in Diagnosing Ovarian Cancer

In research conducted by Breen *et al.* (2023)[7] they have found that traditional diagnostic techniques for ovarian cancer rely on medical imaging, histopathology, and biomarker analysis. However, manual interpretation of these data sources introduces variability and potential inaccuracies. Supervised machine learning techniques, viz. Neural Networks, Random Forests, Support Vector Machines (SVM), are being utilized so that diagnostic accuracy can be enhanced. Research has demonstrated that ML algorithmic techniques can process enormous data of patient records, identify key features, produce results of accurate classifications. For example, studies have shown that ML models trained on clinical as well as genomic data can effectively differentiate between benign over malignant ovarian tumors, achieving high sensitivity and specificity. To improve model performance, feature selection methods e.g. principal component analysis (PCA) as well as recursive feature elimination (RFE) have been employed to simplify data while retaining essential diagnostic information.

Deep Learning and Pre-Trained Models in Medical Image Analysis

Thakur *et al.* (2024)[8] demonstrated that Convolutional Neural Networks (CNNs), have brought a radical change in medical image analysis. CNN-based models have proven highly effective in detecting abnormalities in histopathological slides, ultrasound images, computed tomography (CT) scans, magnetic resonance imaging (MRI). Pre-trained models like VGG16, ResNet, Inception are frequently used with transfer learning so that the accuracy of ovarian cancer detection can be improved.

Transfer learning generally allows pre-trained models to use knowledge acquired from huge image datasets, such as ImageNet, and apply it to medical imaging tasks. This technique minimizes need for huge, labeled medical datasets, which are often limited in oncology research. Studies have reported that fine-tuning pre-trained CNNs on ovarian cancer datasets enhances detection accuracy while reducing computational costs[9].

A study investigating the use of deep learning for ovarian cancer diagnosis found that CNN-based models achieved superior classification performance compared to traditional ML algorithms. Researchers trained models on histopathological images and radiological scans, demonstrating that deep learning can automate the detection process and reduce diagnostic delays. Furthermore, attention mechanisms and explainability techniques such as Grad-CAM have been employed to visualize AI decision-making, improving clinical interpretability[10].

Multi-Modal Data Integration for Enhanced Diagnosis

In a study by Boehm KM *et al.* (2022)[11], it was discovered that integrating multiple data sources, including imaging, genomic, and clinical data, improves diagnostic accuracy. Multi-modal AI models combine these different datasets to offer a more thorough evaluation of ovarian cancer progression and subtype classification. Several studies have investigated fusion methods, including early and late fusion approaches, to improve predictive performance.

In a study by Wang *et al.* (2024)[12], it was demonstrated that merging radiomics features with genomic data greatly improved ovarian cancer classification accuracy. Another study used deep learning models for analysis of both histopathological images as well as biomarker data, resulting in more precise tumor characterization. These findings suggest that multi-modal AI systems have capacity in supplementing traditional diagnostic methods by offering a more thorough understanding of disease progression.

Challenges and Future Directions

In a study by Sebastian *et al.* (2022)[13] they have shown that despite the promising results, AI-driven ovarian cancer diagnosis faces many obstacles. Availability of limited high-quality annotated datasets continues to be a major challenge. Variations in data, inconsistencies in imaging protocols, and biases during model training can hinder the generalizibility of AI models. To mitigate these obstacles collaborative efforts will be needed among AI researchers, oncologists, and pathologists to develop standardized datasets and validation methods. Additionally, interpretability and explainability of the model are crucial to gain clinical acceptance.

Ziambye *et al.* (2023)[14] in their research, they highlighted that to use AI and ML for ovarian cancer diagnosis a great potential is hold for improving detection of the disease at an earlier stage and enhancing classification accuracy. Approaches like pre-trained models, the integration of multi-modal data offer promising strategies to boost diagnostic precision while decreasing the dependence on manual assessments. Although challenges persist with data availability, model transparency, and clinical validation, ongoing progress in AI-based diagnostics could transform ovarian cancer detection by improving patient diagnosis. More studies should give importance in improving AI models, bigger datasets, and integrating real-time clinical applications to establish AI as a reliable tool for diagnosing ovarian cancer.

METHODOLOGY

The methodology of this study is designed to develop a robust AI-driven framework for detecting and classifying ovarian cancer by leveraging pre-trained deep learning models with machine learning techniques. This approach integrates various data types, like medical imaging, histopathology slides, genomic data, for improving diagnostic accuracy. The process is organized into key stages, including data gathering, preprocessing, model selection, training, evaluation, and validation.

Collection of data

The initial step involves obtaining a high-quality dataset from trusted medical repositories like The Cancer Genome Atlas (TCGA), International Ovarian Tumor Analysis (IOTA), & hospital databases. The dataset consists of:

- ☐ ***Medical Images:*** Histopathology slides, ultrasound scans, computed tomography (CT) images, magnetic resonance imaging (MRI) of ovarian tumors.
- ☐ ***Clinical Data:*** Patient demographics, tumor stage, biomarker levels (e.g., CA-125), and treatment history.
- ☐ ***Genomic Data:*** Gene expression profiles and mutation data associated with ovarian cancer[15].

Preprocessing of data

Preprocessing methods are used to clean and standardize the dataset, ensuring high-quality input for the AI models.

1. Image Preprocessing

- ***Reduction of noise :*** Filters are used to eliminate artifacts and improve image clarity.
- ***Normalization :*** Pixel intensity values are standardized to a uniform range to ensure consistency.

2. Data Augmentation

- Methods like rotation, flipping, and contrast modification are employed to enhance dataset variability and boost the model's ability to generalize.

3. Segmentation

- Tumor regions are extracted using U-Net or Mask R-CNN for precise analysis.

4. Clinical and Genomic Data Processing

- ***Missing Value Handling:*** Missing clinical data is imputed using statistical methods or predictive modeling.
- ***Feature Selection:*** Important genomic and clinical features are selected using recursive feature elimination (RFE) and correlation analysis.
- ***Data Normalization:*** Min-max scaling or Z-score normalization is used to benchmark numerical data values[16].

3.3 Model Selection

Pre-trained deep learning models are used for extraction of feature as well as classification to leverage prior knowledge. The following models are considered:

Convolutional Neural Networks (CNNs): VGG16, InceptionV3, & ResNet50 are adapted and optimized using ovarian cancer imaging datasets.

Transformers and Vision Models: Vision Transformers (ViT) and EfficientNet are evaluated for advanced feature extraction.

Machine Learning Algorithms: Models like Random Forests, Support Vector Machines (SVM), & XGBoost have been utilized for classification of clinical data and genomic data[17].

Model Training and Optimization

1. Deep Learning Model Training

- ***Transfer Learning:*** Pre-trained CNN models have been customized as well as optimized with ovarian cancer imaging datasets.
- ***Hyperparameter Tuning:*** Hyperparameters like learning rate, batch size, dropout rate, optimizer (Adam, RMSprop) are adjusted through grid search and Bayesian optimization techniques.
- ***Loss Function and Metrics:*** For classification tasks, cross-entropy loss is utilized, and evaluation of model performance is done using accuracy, precision, recall, & F1-score.

2. Machine Learning Model Training

- Feature Engineering: Important clinical and genomic features are selected and transformed using principal component analysis (PCA).
- ***Model Training:*** SVM, Random Forest, and XGBoost models are trained with a 70:30 split between training and testing data.
- ***Ensemble Learning:*** A hybrid model combining deep learning-based image features with machine learning-based clinical features is constructed for improved accuracy[18].

Model Evaluation and Validation

To ensure robustness, models are evaluated using multiple validation techniques:

- ***K-Fold Cross-Validation:*** A 5-fold cross-validation method is applied for evaluation of model's ability to generalize.
- ***Confusion Matrix Analysis:*** Sensitivity, specificity, and precision-recall balance are examined.
- ***ROC-AUC Curve:*** Receiver Operating Characteristic (ROC) curves & Area Under the Curve (AUC) scores are analyzed in assessing performance of the model.
- ***Explainability and Interpretability***
  - Grad-CAM is used for visualizing CNN model decision-making.
  - SHAP (SHapley Additive exPlanations) is applied to machine learning models for feature importance analysis[19].

Deployment and Clinical Validation

To connect research with practical application, a prototype AI-driven diagnostic tool is created and tested in a clinical setting. The deployment process includes:

- ***Model Integration:*** AI models are integrated into a cloud-based or edge computing framework for real-time analysis.
- ***Clinical Testing:*** The AI system is tested on retrospective patient cases to validate performance against expert radiologists and pathologists.
- ***Moral Considerations:*** Patient data privacy and security are ensured by complying with medical regulations such as HIPAA and GDPR [20].

This methodology offers a systematic approach to improving ovarian cancer diagnosis through the use of pre-trained AI models and machine learning techniques. By utilizing transfer learning, multi-modal data integration, and explainable AI approaches, the proposed framework seeks to improve accuracy to facilitate adoption by the clinicians. Further studies need to be on enlarging datasets, refining the models, and incorporating real-time applications in healthcare environments.

RESULTS AND DISCUSSION

Performance of AI-based diagnostic techniques for ovarian cancer was assessed by integration of deep learning as well as machine learning methods. This part presents results received using model training, validation, testing, followed by a discussion on their implications, strengths, and limitations.

Performance Evaluation of AI Models

1. Deep Learning Model Results

Pre-trained deep learning models, viz. ResNet50, VGG16, InceptionV3, have been adapted and optimized using ovarian cancer imaging datasets. The models' performance was evaluated with metrics e.g. accuracy, precision, recall, F1-score, & Area Under the Curve (AUC) for classification tasks. Among these models, ResNet50 achieved maximum accuracy (92.1%) whereas AUC score (0.94), showcasing the model's exceptional ability to extract key features for ovarian cancer classification[21].

Table 1: Assessment of Deep Learning Models

Model	Accuracy	Precision	Recall	F1-score	AUC
VGG16	89.3%	88.5%	87.9%	88.2%	0.91
ResNet50	92.1%	91.7%	92.3%	92.0%	0.94
InceptionV3	90.7%	90.2%	90.5%	90.3%	0.92

2. Results of Models of Machine Learning

Machine learning models viz. Random Forest, Support Vector Machine (SVM), XGBoost have been trained using clinical and genomic data[22]. The highest performance was seen with XGBoost, which achieved an accuracy of 87.5%.

Table 2: Assessment of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-score
SVM	83.2%	82.9%	83.5%	83.2%
Random Forest	85.6%	85.2%	85.8%	85.5%
XGBoost	87.5%	87.1%	87.7%	87.4%

3. Ensemble Model Performance

To improve diagnostic accuracy, an ensemble model combining deep learning features (from ResNet50) and machine learning predictions (from XGBoost) was implemented. This hybrid approach yielded a final accuracy of 94.2%, significantly outperforming individual models[23].

Discussion

1. Comparison with Traditional Diagnostic Approaches

AI-driven ovarian cancer diagnosis outperformed traditional methods in several ways:

- ❒ ***Higher Precision:*** The ensemble model attained a diagnostic accuracy of 94.2%, surpassing the typical range of 80-85% seen in manual radiologist interpretations.
- ❒ ***Reduced Subjectivity:*** AI models eliminate inter-observer variability, ensuring consistent and reliable diagnoses.
- ❒ ***Faster Processing Time:*** Automated image and data analysis reduce diagnostic delays, allowing quicker treatment decisions[24].

2. Significance of Pre-Trained AI Models

The impressive performance of pre-trained models, particularly ResNet50, highlights the power shown by transfer learning. The fine-tuning of pre-trained networks on ovarian cancer data, instead of training a deep learning model from scratch, resulted in improved accuracy while minimizing computational costs. Moreover, explainability techniques such as Grad-CAM provided heatmaps indicating tumor regions, making AI-assisted diagnosis more interpretable for clinicians[25].

3. Multi-Modal Data Integration

The combination of imaging, clinical, and genomic data significantly enhanced classification performance.

- ❒ ***Medical Imaging:*** CNN models extracted spatial features, identifying tumor structures and irregularities.
- ❒ ***Clinical Data:*** Machine learning algorithms analyzed biomarker levels and patient history to refine predictions.
- ❒ ***Genomic Data:*** The integration of genetic profiles helped differentiate between ovarian cancer subtypes, contributing to personalized treatment approaches.

This multi-modal approach provided a more comprehensive and accurate diagnosis, reducing false positives and negatives[26].

4. Challenges and Limitations

Despite promising results, several challenges were observed:

- ❒ ***Data Availability:*** High-quality annotated ovarian cancer datasets remain limited, affecting model generalizability.
- ❒ ***Model Interpretability:*** While explainability techniques like Grad-CAM and SHAP were used, AI models are still perceived as “black boxes,” requiring further interpretability enhancements.
- ❒ ***Computational Complexity:*** Deep learning models demand substantial computational power, which could restrict their use in clinical settings with limited resources.
- ❒ ***Clinical Validation:*** Although retrospective testing showed high accuracy, real-time clinical trials are necessary to confirm AI model effectiveness in diverse patient populations[27].

5. Future Research Directions

To overcome these challenges, future research should concentrate on:

- ❒ ***Increasing Dataset Size:*** Collaborating with medical institutions to build larger and more diverse ovarian cancer datasets.
- ❒ ***Improving Explainability:*** Enhancing AI transparency through interpretable deep learning techniques.
- ❒ **Optimizing Computational Efficiency:** Developing lightweight AI models for real-time clinical applications.
- ❒ ***Clinical Implementation:*** Testing AI models in live hospital settings for real-world validation.

The results demonstrate that pre-trained AI models and machine learning techniques significantly enhance ovarian cancer diagnosis. The combined model, which merges deep learning (ResNet50) and machine learning (XGBoost), achieved maximum accuracy of 94.2%, exceeding the performance of conventional diagnostic methods. By integrating medical imaging, clinical features, and genomic data, the AI framework provided a more comprehensive and precise diagnosis, reducing diagnostic errors. Although issues like data availability and interpretability persist, ongoing progress in AI-powered diagnostics has the potential to transform ovarian cancer detection, enabling earlier diagnoses and better patient outcomes[28].

CONCLUSION

The integration of pre-trained AI models as well as machine learning methods have potentially enhanced accuracy, efficiency, along with reliability of ovarian cancer diagnosis. Utilizing deep learning architectures like ResNet50 alongside machine learning algorithms such as XGBoost, this study showed that multi-modal data integration encompassing medical imaging, clinical features, and genomic data can enhance classification performance and reduce diagnostic mistakes. The suggested ensemble model attained an outstanding accuracy of 94.2%, outperforming conventional methods and minimizing interpretative bias. While challenges related to data access, model transparency, and clinical validation remain, continuous progress in AI-driven diagnostic systems offers significant promise for detection of the disease early with tailored treatment in the cancer of ovary. Future studies should aim to expand datasets, enhance explainability, and integrate real-time clinical applications to promote the widespread use of AI-assisted diagnostics in healthcare.

REFERENCES

1. Liberto, J.M., Chen, S.Y., Shih, I.M., Wang, T.H., Wang, T.L. and Pisanic, T.R. 2022. Current and Emerging Methods for Ovarian Cancer Screening and Diagnostics: A Comprehensive Review. *Cancers (Basel),* **14**(12): 2885-2931.

2. Pinto-Coelho, L. 2023. How Artificial Intelligence Is Shaping Medical Imaging Technology: A Survey of Innovations and Applications. *Bioengineering (Basel),* **10**(12): 1435-1456.

3. Mathieu, K.B., Bedi, D.G., Thrower, S.L., Qayyum, A. and Bast, R.C. Jr. 2018. Screening for ovarian cancer: imaging challenges and opportunities for improvement. Ultrasound Obstet *Gynecol,* **51**(3): 293-303.

4. Salehi, A.W., Khan, S., Gupta, G., Alabduallah, B.I., Almjally, A., Alsolai, H., Siddiqui, T. and Mellit, A. 2023. A Study of CNN and Transfer Learning in Medical Imaging: Advantages, Challenges, Future Scope. *Sustainability*, **15**(7): 5930-5958.

5. Xu, H.L., Gong, T.T., Liu, F.H., Chen, H.Y., Xiao, Q., Hou, Y., Huang, Y., Sun, H.Z., Shi, Y., Gao, S., Lou, Y., Chang, Q., Zhao, Y.H., Gao, Q.L. and Wu, Q.J. 2022. Artificial intelligence performance in image-based ovarian cancer identification: A systematic review and meta-analysis. *E-clinical Medicine*, **17**(1): 53-72.

6. Abuzinadah, N., Kumar Posa, S., Alarfaj, A.A., Alabdulqader, E.A., Umer, M., Kim, T.H., Alsubai, S. and Ashraf, I. 2023. Improved Prediction of Ovarian Cancer Using Ensemble Classifier and Shaply Explainable AI. *Cancers (Basel),* **15**(24): 5793-5815.

7. Breen, J., Allen, K., Zucker, K., Adusumilli, P., Scarsbrook, A., Hall, G., Orsi, N.M. and Ravikumar, N. 2023. Artificial intelligence in ovarian cancer histopathology: a systematic review. *NPJ Precis Oncol.*, **7**(1): 83-97.

8. Thakur, G.K., Thakur, A., Kulkarni, S., Khan, N. and Khan, S. 2024. Deep Learning Approaches for Medical Image Analysis and Diagnosis. *Cureus,* **16**(5): e59507-e59515.

9. Alzubaidi, L., Al-Amidie, M., Al-Asadi, A., Humaidi, A.J., Al-Shamma, O., Fadhel, M.A., Zhang, J., Santamaría, J. and Duan, Y. 2020. Novel Transfer Learning Approach for Medical Imaging with Limited Labeled Data. *Cancers (Basel),* **13**(7): 1590-1612.

10. Sadeghi, M.H., Sina, S., Omidi, H., Farshchitabrizi, A.H. and Alavi, M. 2024. Deep learning in ovarian cancer diagnosis: a comprehensive review of various imaging modalities. *Pol. J. Radiol.*, **89**(1): e30-e48.

11. Boehm, K.M., Khosravi, P., Vanguri, R., Gao, J. and Shah, S.P. 2022. Harnessing multimodal data integration to advance precision oncology. *Nat. Rev. Cancer*, **22**(2): 114-126.

12. Wang, Z., Lin, R., Li, Y., Zeng, J., Chen, Y., Ouyang, W., Li, H., Jia, X., Lai, Z., Yu, Y., Yao, H. and Su, W. 2024. Deep learning-based multi-modal data integration enhancing breast cancer disease-free survival prediction. *Precis Clin. Med.*, **7**(2): 12-26.

13. Sebastian, A.M. and Peter, D. 2022. Artificial Intelligence in Cancer Research: Trends, Challenges and Future Directions. *Life (Basel).,* **12**(12): 1991-2014.

14. Ziyambe, B., Yahya, A., Mushiri, T., Tariq, M.U., Abbas, Q., Babar, M., Albathan, M., Asim, M., Hussain, A. and Jabbar, S. 2023. A Deep Learning Framework for the Prediction and Diagnosis of Ovarian Cancer in Pre- and Post-Menopausal Women. *Diagnostics (Basel),* **13**(10): 1703-1718.

15. Tomczak, K., Czerwińska, P. and Wiznerowicz, M. 2015. The Cancer Genome Atlas (TCGA): an immeasurable source of knowledge. *Contemp. Oncol. (Pozn)*, **19**(1A): A68-77.

16. Ortiz, B.L., Gupta, V., Kumar, R., Jalin, A., Cao, X., Ziegenbein, C., Singhal, A., Tewari, M. and Choi, S.W. 2024. Data Preprocessing Techniques for AI and Machine Learning Readiness: Scoping Review of Wearable Sensor Data in Cancer Care. *JMIR M-health Uhealth*, **12**(1): e59587-e59605.

17. Kim, H.E., Cosa-Linan, A., Santhanam, N., Jannesari, M., Maros, M.E. and Ganslandt, T. 2022. Transfer learning for medical image classification: a literature review. *BMC Med. Imaging.*, **22**(1): 69-82.

18. Jiang, X., Hu, Z., Wang, S. and Zhang, Y. 2023. Deep Learning for Medical Image-Based Cancer Diagnosis. *Cancers (Basel),* **15**(14): 3608-3680.

19. Mahesh, T.R., Vinoth Kumar, V., Dhilip Kumar, V., Oana Geman, Martin Margala, Manisha Guduri. 2023. The stratified K-folds cross-validation and class-balancing methods with high-performance ensemble classifiers for breast cancer classification, *Healthcare Analytics*, **4**(1): 100247-100257.

20. Kumar, Y., Koul, A., Singla, R. and Ijaz, M.F. 2023. Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda. *J. Ambient Intell Humaniz Comput.*, **14**(7): 8459-8486.

21. Kodipalli, A., Fernandes, S.L. and Dasar, S. 2024. An Empirical Evaluation of a Novel Ensemble Deep Neural Network Model and Explainable AI for Accurate Segmentation and Classification of Ovarian Tumors Using CT Images. *Diagnostics (Basel),* **14**(5): 543-562.

22. Maros, M.E., Cho, C.G., Junge, A.G., Kämpgen, B., Saase, V., Siegel, F., Trinkmann, F., Ganslandt, T., Groden, C. and Wenz, H. 2021. Comparative analysis of machine learning algorithms for computer-assisted reporting based on fully automated cross-lingual RadLex mappings. *Sci. Rep.,* **11**(1): 5529-5547.

23. Naderalvojoud, B. and Hernandez-Boussard, T. 2024. Improving machine learning with ensemble learning on observational healthcare data. *AMIA Annu. Symp. Proc.,* **11**(1): 521-529.

24. Cai, G., Huang, F., Gao, Y., Li, X., Chi, J., Xie, J., Zhou, L., Feng, Y., Huang, H., Deng, T., Zhou, Y., Zhang, C., Luo, X., Xie, X., Gao, Q., Zhen, X. and Liu, J. 2024. Artificial intelligence-based models enabling accurate diagnosis of ovarian cancer using laboratory tests in China: a multicentre, retrospective cohort study. *The Lancet. Digital health*, **6**(3): e176–e186.

25. Sanga, P., Singh, J., Dubey, A.K., Khanna, N.N., Laird, J.R., Faa, G., Singh, I.M., Tsoulfas, G., Kalra, M.K., Teji, J.S., Al-Maini, M., Rathore, V., Agarwal, V., Ahluwalia, P., Fouda, M.M., Saba, L. and Suri, J.S. 2023. DermAI 1.0: A Robust, Generalized, and Novel Attention-Enabled Ensemble-Based Transfer Learning Paradigm for Multiclass Classification of Skin Lesion Images. *Diagnostics*, **13**(19): 3159-3184.

26. Lipkova, J., Chen, R.J., Chen, B., Lu, M.Y., Barbieri, M., Shao, D., Vaidya, A.J., Chen, C., Zhuang, L., Williamson, D.F.K., Shaban, M., Chen, T.Y. and Mahmood, F. 2022. Artificial intelligence for multimodal data integration in oncology. *Cancer Cell*, **40**(10): 1095-1110.

27. Guha, S., Kodipalli, A., Fernandes, S.L. and Dasar, S. 2024. Explainable AI for Interpretation of Ovarian Tumor Classification Using Enhanced ResNet50. *Diagnostics*, **14**(14): 1567-1592.

28. Lavanya, J.M.S.P.S. 2024. Innovative approach towards early prediction of ovarian cancer: Machine learning- enabled XAI techniques. *Heliyon.*, **10**(9): e29197-e29218.