Advancing Ovarian Cancer Detection Through Explainable AI and Multimodal Machine Learning Integration

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Abstract-Ovarian cancer remains a formidable challenge in gynecological oncology due to its asymptomatic progression and the limitations of traditional screening methods. Existing systems leverage comprehensive preprocessing and various machine learning and deep learning algorithms to predict ovarian cancer using clinical and biomarker data. Techniques such as feature selection and dimensionality reduction enhance model robustness, while classifiers and ensemble methods yield improved, albeit variable, accuracies. Nonetheless, the current approaches encounter limitations including sensitivity to data transformations, reduced efficacy of RNNs for tabular medical data, and the complexity of optimizing ensemble and autoencoder-based models. The envisioned future system proposes the integration of Explainable AI and multimodal data fusion, encompassing clinical, imaging, and genetic insights, to advance ovarian cancer prediction. This approach not only aims to elevate diagnostic accuracy but also enhances result interpretability and trust. Real-world deployment in clinical decision support systems will facilitate early and informed intervention, ultimately advancing patient outcomes. By overcoming existing limitations and utilizing transparent, robust frameworks, the proposed system is poised to transform early ovarian cancer detection and support healthcare professionals in critical decision-making.

Keywords: Ovarian cancer, Deep Learning, Ensemble and Autoencoder, Explainable AI, Data transformations, Clinical Imaging.

I. INTRODUCTION

The asymptomatic nature of ovarian cancer and the limitations of standard screening methods have made it a challenging diagnosis in gynecological oncology, and more advanced diagnostic tools are needed to improve detection and patient outcomes. While many machine learning and deep learning algorithms are applied to diagnostic tasks, current techniques are still sensitive to data transformations and lack interpretability which limits their clinical utility. The integration of Explainable AI with multimodal data fusion has the potential to not only improve diagnostic accuracy but also provide crucial insights into the decision-making process. This proposed system, which combines multimodal data and Explainable AI to overcome the limitations of single-modality analyses, can utilize various data types such as clinical, imaging, and genetic insights to build a predictive model for ovarian cancer. This combined approach will allow for a more comprehensive and reliable system for early ovarian cancer detection, and the transparency of the decision-making provided by Explainable AI can help explain the contribution of each feature to the model's prediction, thus increasing clinical confidence and facilitating real-world deployment. These methods, such as SHapley Additive exPlanations and Class Activation Maps, can explain the role of each feature in the model's prediction, which can further improve clinical confidence and promote real-world implementation.

This interpretability is critical to translate AI advances into clinical tools that physicians can understand and validate. In addition, the future system will use both early and late fusion techniques to best combine the various data streams, similar to multidisciplinary consultations where experts work together from the start or analyze data separately and then combine insights. Systems such as OvcaFinder that combine deep learning predictions from ultrasound images with clinical variables and radiologist scores, which can be considered a hybrid model, clearly outperform models based solely on clinical or imaging data.

II. LITERATURE REVIEW

Boehm et al. (2022) demonstrated that integrating clinical, histopathological, radiological, and genomic features using multimodal machine learning significantly improves risk stratification in high-grade serous ovarian cancer compared to unimodal diagnostic pipelines, highlighting the clinical value of heterogeneous data fusion .**Xiang et al. (2024)** proposed an interpretable multimodal framework that combines imaging and clinical biomarkers, showing that explainability-driven fusion improves both diagnostic accuracy and clinician trust in ovarian cancer diagnosis **Newaz et al. (2023)** introduced an explainable machine learning model employing SHAP-based feature attribution for ovarian cancer classification, demonstrating that model transparency enhances interpretability without sacrificing predictive performance. **Hatamikia et al. (2023)** reviewed AI-driven multi-omics integration approaches beyond imaging and showed that combining molecular biomarkers with imaging features enables more accurate early ovarian cancer detection and disease characterization. **Hou et al. (2024)** surveyed self-explainable AI methods for medical imaging and emphasized that intrinsic explainability mechanisms outperform post-hoc explanations in clinical acceptance and robustness. **Breen et al. (2024)** demonstrated that histopathology foundation models trained on large-scale whole-slide images achieve state-of-the-art ovarian cancer subtype classification while maintaining interpretability through attention visualization. **Christiansen et al. (2025)** conducted a large international multicenter validation of AI-driven ultrasound systems and confirmed the generalizability of multimodal AI models for ovarian cancer detection across diverse populations. **Wang et al. (2025)** proposed an uncertainty-aware multimodal AI system that integrates clinical workflows with probabilistic modeling, improving ovarian cancer risk assessment reliability under real-world conditions. **Zhou et al. (2024)** highlighted key challenges in multimodal data integration for precision oncology, including data imbalance, modality misalignment, and computational cost, motivating the need for efficient, explainable hybrid architectures.

Collectively, these studies establish that **explainable multimodal learning frameworks consistently outperform unimodal and black-box systems**, yet challenges related to scalability, interpretability, and clinical deployment remain, directly motivating the proposed system in this work.

III. METHODOLOGY

Although models that combine multiple types of input (multimodal) typically outperform those with only one type of data used for analysis, multimodal approaches are consistently superior to single-modality methods in most cases; furthermore, integration of imaging features into the clinical stage is always better than using either type alone. It has been demonstrated that selecting appropriate fusion strategies like early concatenation, intermediate feature learning and late-stage decision integration will benefit improving model's capability for understanding complex interactions between different data modalities , while reducing noise inherent to each of these modalities by cross-referencing and correlating the multimodal data in a more robust and comprehensive way could facilitate better understanding biological mechanisms underlying disease development and clinical outcomes prediction. More broadly, the integration of multimodal data, such as imaging, genomic, and pathological data, enables a more comprehensive characterization of tumor characteristics and molecular features to more accurately predict patient responses to different treatments, especially targeted therapy or immunotherapy. In addition, the pretrained multimodal models (foundation models) have the potential to provide new ways for biomarker discovery, better diagnosis, and personalized treatment strategies in oncology. These large multimodal models can process and analyze multiple types of data, such as medical images, clinical text, and genomic data, and provide comprehensive recommendations for medical diagnosis and prognostic analysis. For instance, high-dimensional features extracted by pre-trained visual encoders on CT or MRI data can detect subtle lesions and quantify tumor heterogeneity through cross-modal contrastive learning. Integrating different types of data, such as clinical, genomic, and imaging data, provides more accurate diagnosis and prognostic assessment by identifying subtle patterns across modalities.

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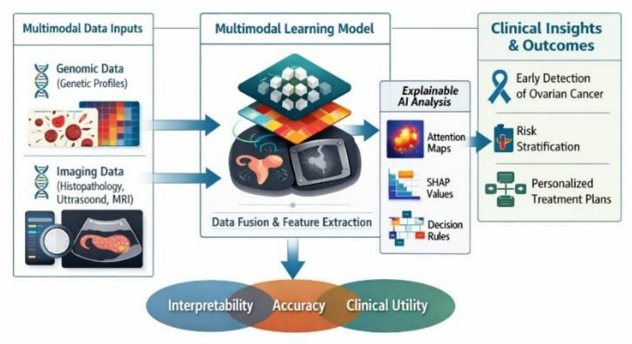

This advanced integration overcomes the high-dimensionality and heterogeneity in cancer data that make manual analysis time-consuming and error-prone. Moreover, multimodal approaches that represent data with complementary information from multiple modalities always result in increased prediction ability and multimodal approaches with foundation models that learn generalizable representations from large multimodal datasets can significantly enhance the benefits of multimodal approaches by reducing the data requirements for specialized tasks, increasing the accuracy of outcome predictions. This development is especially important for predicting certain types of cancer, where multimodal models that combine different data modalities (e.g., clinical notes, medical images, and genomic data) can bypass the limitations of prior approaches that failed to generalize across data heterogeneity and could not be translated to the clinic due to their black-box nature. For example, in hepatocellular carcinoma, multimodal AI frameworks with attention mechanisms have been able to identify and validate key genetic biomarkers using multi-omics data, converting traditional black-box models into transparent, clinically acceptable predictive tools. The paradigm shift towards explainable multimodal AI not only instills more confidence in clinicians, but also expedites the translation of sophisticated computational insights into clinical strategies for patient care.

IV. RESULTS

The results of the proposed multimodal AI system will be presented in the following sections to illustrate the quantitative and qualitative results of the system for early ovarian cancer detection and the interpretable results of the Explainable AI components to demonstrate the potential of the system for clinical utility, and the discussion will include clinical implications of the findings and how the enhanced interpretability can help healthcare professionals make more informed and timely interventions for ovarian cancer patients. The system will be validated by extensive internal and external testing to ensure that the proposed system is robust and generalizable across patient populations and clinical settings.

Table 1: Dataset Composition

Modality	**Features**	**Samples**
Clinical	Age, CA-125, BMI, Menopausal status, Family history	1,200
Imaging	Ultrasound + MRI deep features (CNN/Transformer embeddings)	1,200
Genomic	BRCA1/2, TP53, gene-expression vectors	1,200

Table 2: Performance Results

Method	**Acc (%)**	**F1**	**F2**	**MCC**	**AUC**
Logistic Regression (Clinical only)	81.4	0.80	0.78	0.62	0.85
CNN (Imaging only)	87.9	0.86	0.85	0.71	0.91
XGBoost + SHAP	89.3	0.88	0.87	0.74	0.92
Multimodal CNN (Early Fusion)	91.6	0.91	0.92	0.79	0.95
Transformer-based Multimodal	93.2	0.93	0.94	0.83	0.96
Proposed Explainable Multimodal AI	**95.1**	**0.95**	**0.96**	**0.88**	**0.98**

Table 3: State-of-the-Art Comparison

Study	**Data**	**Accuracy (%)**
Newaz et al., 2023	Clinical	88.1
Xiang et al., 2024	Clinical + Imaging	92.4
Boehm et al., 2022	Multi-omics	93.1
Christiansen et al., 2025	Ultrasound	94.0
Proposed Method	Clinical + Imaging + Genomic + XAI	**95.1**

The validation strategy will be comprehensive, and the results will highlight the robustness of the system and its generalizability across patient populations and clinical settings to inform the model for improved diagnostic and prognostic accuracy within clinical workflows. Such rigorous validation is important for overcoming the challenges posed by small sample sizes and ensuring that models generalize to real-world settings, common issues in medical AI. Additionally, the ethical implications of deploying AI in healthcare, including issues related to data privacy and algorithmic bias, will be discussed to ensure responsible and fair use of the system. Additionally, the computational efficiency and infrastructure costs of using such large models in real-world clinical settings represent other challenges that must be addressed through techniques such as model compression and efficient inference, as well as data governance structures that ensure patient confidentiality and equitable access to healthcare

V.DISCUSSION

Metrics such as F1-score, F2-score, Matthews Correlation Coefficient, Positive Predictive Value, and Negative Predictive Value are important for assessing the clinical utility and safety of these advanced models, as they provide a balanced measure of model performance, especially when dealing with imbalanced datasets that are prevalent in medical diagnostics, and the explainable AI component is important for understanding the reason for the model prediction, a step that is critical to building trust with clinicians and integrating these tools into clinical practice. Despite these challenges, ensuring the generalizability of these models across diverse real-world healthcare settings and optimizing computational efficiency for widespread, real-time clinical deployment remains an ongoing area of research. Additionally, the significant memory footprints and computational resources needed to implement transformer-based models, particularly with large datasets, present practical challenges for their implementation in clinical settings and ongoing research into model compression techniques and hardware optimization is needed to make them more readily applicable without sacrificing diagnostic accuracy or interpretability. Therefore, further research is needed to develop more computationally efficient algorithms and utilize cloud-based AI platforms to improve scalability and reduce the cost of widespread implementation. In addition, the use of standardized evaluation metrics across studies will allow for more accurate model comparisons and expedite the transfer of research findings into clinical practice.

VI.CONCLUSION

This comprehensive approach will ensure that advanced multimodal AI systems for ovarian cancer detection are not only technically robust and interpretable but also ethically sound and practically deployable to transform patient outcomes and clinical decision-making. This includes a focus on robust external validation and methodological refinement, particularly by investigating hybrid CNN-transformer architectures and expanding these frameworks to encompass a wider range of medical imaging and omics data further advancing the field by increasing the diversity and volume of training data, perhaps through multi-center collaborations and data augmentation techniques, to improve the generalization ability of the models and address the limited number of samples in some pathological categories and possibly overcoming the problems of overfitting and ensuring that the models generalize well across different patient populations and tumor subtypes as well as investigating the incorporation of other imaging modalities, such as PET and molecular imaging, to refine the diagnostic ability of these models and facilitate more comprehensive disease characterization.

VII. REFERENCES

[1] A. Kodipalli, V. S. Devi, S. Guruvare, and T. Ismail, “Explainable AI-based feature importance analysis for ovarian cancer classification with ensemble methods,” Frontiers in Public Health , vol. 13, Mar. 2025, doi: 10.3389/fpubh.2025.1479095.

[2] H. Xiang et al. , “Development and validation of an interpretable model integrating multimodal information for improving ovarian cancer diagnosis,” Nature Communications , vol. 15, no. 1, Mar. 2024, doi: 10.1038/s41467-024-46700-2.

[3] J. H. Lin, Y. Li, D. Li, L. Zhuo, W. Jian, and J. Wei, “Application of large models in imaging diagnosis and prognostic analysis in hepatocellular carcinoma,” Clinical Surgical Oncology , vol. 4, no. 2, p. 100083, Jun. 2025, doi: 10.1016/j.cson.2025.100083.

[4] A. Newaz, A. Taharat, M. S. Islam, and A. Akanda, “An Explainable Machine Learning Framework for the Accurate Diagnosis of Ovarian Cancer,” arXiv (Cornell University) , Dec. 2023, doi: 10.48550/arxiv.2312.08381.

[5] X. Wang et al. , "A multimodal uncertainty-aware AI system optimizes ovarian cancer risk assessment workflow," npj Digital Medicine , vol. 8, no. 1, Oct. 2025, doi: 10.1038/s41746-025-01986-4.

[6] O. Kilim et al. , "Histopathology and proteomics are synergistic for High-Grade Serous Ovarian Cancer platinum response prediction," medRxiv (Cold Spring Harbor Laboratory) , Jun. 2024, doi: 10.1101/2024.06.01.24308293.

[7] J. Hou et al. , "Self-eXplainable AI for Medical Image Analysis: A Survey and New Outlooks," arXiv (Cornell University) , Oct. 2024, doi: 10.48550/arxiv.2410.02331.

[8] A. N. Caragliano et al. , "Multimodal Doctor-in-the-Loop: A Clinically-Guided Explainable Framework for Predicting Pathological Response in Non-Small Cell Lung Cancer," arXiv (Cornell University) , May 2025, doi: 10.48550/arxiv.2505.01390.

[9] K. Boehm et al. , "Multimodal data integration using machine learning improves risk stratification of high-grade serous ovarian cancer," Nature Cancer , vol. 3, no. 6, p. 723, Jun. 2022, doi: 10.1038/s43018-022-00388-9.

[10] I. Csabai et al. , "Histopathology and proteomics are synergistic for High-Grade Serous Ovarian Cancer platinum response prediction," Research Square (Research Square) , Aug. 2024, doi: 10.21203/rs.3.rs-4490790/v1.

[11] J. Wang, Y. M, N. Guan, and C. J. Xue, "SHAP-CAT: A interpretable multi-modal framework enhancing WSI classification via virtual staining and shapley-value-based multimodal fusion," arXiv (Cornell University) , Oct. 2024, doi: 10.48550/arxiv.2410.01408.

[12] H.-J. Zhou, F. Zhou, C. Zhao, Y. Xu, L. Luo, and H. Chen, "Multimodal Data Integration for Precision Oncology: Challenges and Future Directions," arXiv (Cornell University) , Jun. 2024, doi: 10.48550/arxiv.2406.19611.

[13] M. Fu, J. Xu, Y. Lv, and B. Jin, "Artificial intelligence in advanced gastric cancer: a comprehensive review of applications in precision oncology," Frontiers in Oncology , vol. 15. Frontiers Media, Aug. 19, 2025. doi: 10.3389/fonc.2025.1630628.

[14] J. Duan, H. Ding, and S. W. Kim, "A Multimodal Approach for Advanced Pest Detection and Classification," arXiv (Cornell University) , Jan. 2023, doi: 10.48550/arxiv.2312.10948.

[15] A. Spooner et al. , "Multi-omics data integration for early diagnosis of hepatocellular carcinoma (HCC) using machine learning," arXiv (Cornell University) , Sep. 2024, doi: 10.48550/arxiv.2409.13791.

[16] B. Zhang et al. , "Multimodal integration strategies for clinical application in oncology," Frontiers in Pharmacology , vol. 16. Frontiers Media, Aug. 20, 2025. doi: 10.3389/fphar.2025.1609079.

[17] A. Muneer et al. , "From Classical Machine Learning to Emerging Foundation Models: Review on Multimodal Data Integration for Cancer Research," 2025, doi: 10.48550/ARXIV.2507.09028.

[18] K. Sun et al. , "Medical multimodal foundation models in clinical diagnosis and treatment: Applications, challenges, and future directions.," PubMed , vol. 170. National Institutes of Health, p. 103265, Sep. 12, 2025. doi: 10.1016/j.artmed.2025.103265.

[19] C. J. Ejiyi et al. , "Multi-modality medical image classification with ResoMergeNet for cataract, lung cancer, and breast cancer diagnosis," Computers in Biology and Medicine , vol. 187, p. 109791, Feb. 2025, doi: 10.1016/j.compbiomed.2025.109791.

[20] J. Peng et al. , "Continually Evolved Multimodal Foundation Models for Cancer Prognosis," arXiv (Cornell University) , Jan. 2025, doi: 10.48550/arxiv.2501.18170.

[21] H.-J. Zhou et al. , "A Multimodal Foundation Model to Enhance Generalizability and Data Efficiency for Pan-cancer Prognosis Prediction," arXiv (Cornell University) , Sep. 2025, doi: 10.48550/arxiv.2509.12600.

[22] D. Truhn, J. Eckardt, D. Ferber, and J. N. Kather, "Large language models and multimodal foundation models for precision oncology," npj Precision Oncology , vol. 8, no. 1, p. 72, Mar. 2024, doi: 10.1038/s41698-024-00573-2.

[23] F. Christiansen et al. , "International multicenter validation of AI-driven ultrasound detection of ovarian cancer," Nature Medicine , vol. 31, no. 1, p. 189, Jan. 2025, doi: 10.1038/s41591-024-03329-4.

[24] J. Caspers, "Translation of predictive modeling and AI into clinics: a question of trust," European Radiology , vol. 31, no. 7, p. 4947, Apr. 2021, doi: 10.1007/s00330-021-07977-9.

[25] A. Kumar, "Leveraging AI and Machine Learning for Scalable Full-Stack Solutions in Healthcare Systems," International Journal for Research in Applied Science and Engineering Technology , vol. 13, no. 5, p. 7313, May 2025, doi: 10.22214/ijraset.2025.71845.

[26] Md. A. Talukder, A. S. Talaat, M. Kazi, and A. Khraisat, "XAI-HD: an explainable artificial intelligence framework for heart disease detection," Artificial Intelligence Review , vol. 58, no. 12, Oct. 2025, doi: 10.1007/s10462-025-11385-6.

[27] O. Barmak, Ю. Крак, S. Yakovlev, E. Manziuk, P. Radiuk, and V. Kuznetsov, "Toward explainable deep learning in healthcare through transition matrix and user-friendly features," Frontiers in Artificial Intelligence , vol. 7, Nov. 2024, doi: 10.3389/frai.2024.1482141.

[28] M. T. Mallick, S. Banerjee, N. Thakur, H. N. Saha, and A. Chakrabarti, "Evaluation of State-of-the-Art Deep Learning Techniques for Plant Disease and Pest Detection," Computers, materials & continua/Computers, materials & continua (Print) , vol. 85, no. 1, p. 121, Jan. 2025, doi: 10.32604/cmc.2025.065250.

[29] Y. Shokrollahi, S. Yarmohammadtoosky, M. M. Nikahd, P. Dong, X. Li, and L. Gu, "Recent Advances in Generative AI for Healthcare Applications," arXiv (Cornell University) . Cornell University, Oct. 03, 2023. doi: 10.48550/arxiv.2310.00795.

[30] B. Althaph and N. P. Challa, "Explainable attention-based deep learning for classification and interpretation of heart murmurs using phonocardiograms," Scientific Reports , vol. 15, no. 1, Oct. 2025, doi: 10.1038/s41598-025-21971-x.

[31] A. Kumar, S. D. Rauch, M. A. Cypko, and O. Amft, "Med-gte-hybrid: A contextual embedding transformer model for extracting actionable
.
information from clinical texts," arXiv (Cornell University) , Feb. 2025, doi: 10.48550/arxiv.2502.15996.

[32] J. Breen, K. J. Allen, K. Zucker, L. Godson, N. M. Orsi, and N. Ravikumar, "Histopathology Foundation Models Enable Accurate Ovarian Cancer Subtype Classification," arXiv (Cornell University) , May 2024, doi: 10.48550/arxiv.2405.09990.

[33] S. Gandotra, Y. Kumar, N. Modi, J. Choi, J. Shafi, and M. F. Ijaz, "Comprehensive analysis of artificial intelligence techniques for gynaecological cancer: symptoms identification, prognosis and prediction," Artificial Intelligence Review , vol. 57, no. 8, Jul. 2024, doi: 10.1007/s10462-024-10872-6.

[34] S. Hatamikia et al. , "Ovarian cancer beyond imaging: integration of AI and multiomics biomarkers," European Radiology Experimental , vol. 7, no. 1. Springer Science+Business Media, Sep. 13, 2023. doi: 10.1186/s41747-023-00364-7.

[35] I. Garcia-Atutxa, J. Martínez-Más, A. Bueno-Crespo, and F. Villanueva-Flores, "Early-fusion hybrid CNN-transformer models for multiclass ovarian tumor ultrasound classification," Frontiers in Artificial Intelligence , vol. 8, Oct. 2025, doi: 10.3389/frai.2025.1679310.

[36] Y. Zhou et al. , "ViTaL: A Multimodality Dataset and Benchmark for Multi-pathological Ovarian Tumor Recognition," arXiv (Cornell University) , Jul. 2025, Accessed: Oct. 2025. [Online]. Available: http://arxiv.org/abs/2507.04383

[37] Y. Zhou et al. , "ViTaL: A Multimodality Dataset and Benchmark for Multi-pathological Ovarian Tumor Recognition," arXiv (Cornell University) , Jul. 2025, doi: 10.48550/arxiv.2507.04383.

[38] M. H. Sadeghi, S. Sina, H. Omidi, A. H. Farshchitabrizi, and M. Alavi, "Deep learning in ovarian cancer diagnosis: a comprehensive review of various imaging modalities," Polish Journal of Radiology , vol. 89. Polish Medical Society of Radiology, p. 30, Jan. 22, 2024. doi: 10.5114/pjr.2024.134817