International Journal of ADVANCED RESEARCH & INNOVATIONS

Volume 14, Issue-12
December, 2024, P06
ISSN: 2319-9253

THE NEXT GENERATION OF COMPUTATIONAL ONCOLOGY: EXPLAINABLE, MULTIMODAL, AND FEDERATED ARTIFICIAL INTELLIGENCE

[#1]**Dr. Prakash Nambiar**, Professor, Department of Neurology,
KIMS Medical College, Thiruvananthapuram, India
Prakashnambiar83@gmail.com

[#2]**Dr. Shweta Gupta**, Associate Professor, Department of Pharmacology,
KIMS Medical College, Thiruvananthapuram, India
Shwetagupta44@gmail.com

[#3] **Dr. Imran Khan**, Assistant Professor, Department of Radiodiagnosis,
KIMS Medical College, Thiruvananthapuram, India
Imrankhan208@gmail.com

Abstract: Computational oncology is undergoing a profound transformation driven by the convergence of explainable artificial intelligence (XAI), multimodal foundation models, federated learning, and precision medicine. Conventional machine learning approaches have substantially improved cancer diagnosis, prognostic prediction, and therapeutic planning but often remain constrained by limited interpretability, fragmented analysis of heterogeneous biomedical information, and restricted generalizability across healthcare systems. The next generation of computational oncology addresses these limitations through intelligent AI ecosystems capable of integrating radiological imaging, digital pathology, genomics, transcriptomics, proteomics, metabolomics, epigenomics, spatial biology, laboratory biomarkers, liquid biopsy, wearable physiological monitoring, electronic health records, patient-reported outcomes, and longitudinal clinical data into unified patient-specific computational representations. Explainable AI enhances transparency and clinician trust, multimodal learning enables systems-level biological understanding, and federated learning facilitates collaborative model development while preserving patient privacy. Together with graph neural networks, multimodal transformers, self-supervised learning, digital twins, reinforcement learning, multimodal large language models, retrieval-augmented generation, and agentic AI, these technologies establish intelligent computational ecosystems capable of supporting precision diagnosis, biomarker discovery, therapeutic optimization, adaptive disease monitoring, and evidence-based clinical decision support. Despite remarkable technological advances, important scientific, technical, ethical, and regulatory challenges remain regarding multimodal data harmonization, computational scalability, interoperability, cybersecurity, clinical validation, governance, and equitable implementation. This review provides a comprehensive overview of the next generation of computational oncology, emphasizing explainable, multimodal, and federated artificial intelligence as the computational foundation of future precision cancer medicine.[1]

Keywords: *Computational oncology, Explainable artificial intelligence, Federated learning, Foundation models, Multimodal learning, Precision oncology, Clinical decision support, Digital pathology, Radiomics, Personalized medicine.*

1. Introduction

Cancer is a biologically heterogeneous disease characterized by continuous interactions among genomic instability, epigenetic regulation, transcriptional activity, protein signaling, immune adaptation, metabolic reprogramming, tissue remodeling, environmental influences, and host physiology. These interconnected biological processes evolve throughout diagnosis, treatment, recurrence, metastasis, and survivorship, making oncology increasingly dependent upon advanced computational intelligence capable of integrating diverse biomedical information.[2]

Modern oncology generates enormous quantities of heterogeneous data through radiological imaging, digital pathology, genomic sequencing, transcriptomics, proteomics, metabolomics, spatial biology, laboratory medicine, wearable physiological monitoring, electronic health records, physician documentation, and patient-reported outcomes. Although each modality provides valuable biological insight, isolated interpretation frequently overlooks the systems-level interactions governing disease progression, therapeutic response, and long-term clinical outcomes.[3]

Artificial intelligence has emerged as a transformative computational technology capable of integrating these heterogeneous biomedical datasets into unified patient-centered representations. Recent advances in explainable AI, multimodal foundation models, and federated learning have substantially expanded these capabilities by improving interpretability, biological integration, collaborative model development, and clinical generalizability.[4]

The convergence of these technologies defines the next generation of computational oncology as an intelligent, transparent, privacy-preserving, and continuously adaptive ecosystem supporting precision cancer medicine throughout the patient journey.[5]

2. Evolution of Computational Oncology

The earliest applications of computational oncology primarily relied on statistical analyses and rule-based decision-support systems developed for individual diagnostic or prognostic tasks. Although these approaches improved clinical decision-making, they frequently lacked scalability, adaptability, and comprehensive biological integration.[6]

Machine learning subsequently enabled predictive modeling using engineered biomedical features, while deep learning substantially improved automated interpretation of radiological imaging, digital pathology, genomic sequencing, and clinical documentation. Transformer architectures further revolutionized biomedical artificial intelligence through generalized representation learning across heterogeneous biomedical datasets.

Foundation AI models have now transformed computational oncology by acquiring transferable biomedical knowledge through large-scale self-supervised learning before adaptation to specialized oncology applications. Simultaneously, explainable AI, federated learning, digital twins, reinforcement learning, multimodal large language models, and agentic AI have established integrated computational ecosystems capable of supporting comprehensive precision oncology.

These technological advances collectively define the emergence of next-generation computational oncology.[7]

3. Principles of Next-Generation Computational Oncology

Next-generation computational oncology is founded upon three complementary computational principles: multimodal intelligence, explainable decision-making, and collaborative federated learning. Rather than functioning as isolated predictive algorithms, foundation AI models integrate heterogeneous biomedical information into unified patient-specific computational representations supporting systems-level biological reasoning.[8]

Self-supervised learning enables discovery of latent biological relationships without requiring extensive manual annotation, while multimodal transformer architectures align radiological imaging, digital pathology, genomics, transcriptomics, proteomics, metabolomics, laboratory biomarkers, wearable physiological monitoring, physician documentation, and longitudinal clinical trajectories within shared computational embedding spaces.

Graph neural networks further model biological interactions among genes, proteins, signaling pathways, immune populations, imaging phenotypes, tissue architecture, therapeutic targets, physiological variables, and clinical

Paper Available at: www.ijarai.com
DOI : https://doi.org/10.65713/ijaraiv14i1206

outcomes, thereby supporting comprehensive precision oncology while explainable AI ensures computational transparency and federated learning enables collaborative intelligence across healthcare systems.[9]

4. Computational Architecture

Modern computational oncology platforms consist of interconnected computational layers responsible for multimodal biomedical data acquisition, preprocessing, representation learning, explainable reasoning, federated collaboration, adaptive learning, predictive analytics, digital twin simulation, and intelligent clinical decision support.[10]

The acquisition layer continuously incorporates radiological imaging, digital pathology, genomic sequencing, transcriptomics, proteomics, metabolomics, epigenomics, spatial biology, laboratory investigations, circulating tumor DNA, wearable physiological monitoring, medication history, patient-reported outcomes, and electronic health records. Advanced preprocessing pipelines normalize imaging studies, harmonize molecular datasets, encode clinical narratives using natural language processing, and synchronize temporal patient information.

Foundation AI models subsequently generate generalized multimodal embeddings representing molecular biology, tissue architecture, imaging phenotypes, physiological function, and longitudinal clinical trajectories. Explainability modules, federated optimization algorithms, and adaptive learning systems collectively support trustworthy, collaborative, and continuously evolving computational oncology.[11]

5. Multimodal Foundation Models

Foundation AI models represent the computational core of next-generation oncology because they acquire generalized biomedical knowledge from large-scale multimodal datasets before specialization for individual clinical applications. Unlike conventional task-specific algorithms, foundation models develop transferable computational representations applicable across diagnosis, prognosis, biomarker discovery, therapeutic prediction, disease monitoring, computational pathology, radiomics, immunotherapy, and intelligent clinical decision support.[12]

Transformer architectures enable multimodal attention across imaging, pathology, molecular biology, laboratory investigations, wearable monitoring, and clinical documentation, while graph neural networks characterize biological interactions among signaling pathways, immune responses, imaging phenotypes, therapeutic targets, physiological variables, and longitudinal clinical outcomes.

These generalized computational capabilities substantially improve robustness, transfer learning, few-shot learning, and clinical generalizability across diverse healthcare environments while strengthening precision oncology.[13]

6. Explainable Artificial Intelligence

Clinical implementation of artificial intelligence requires transparency, interpretability, and clinician confidence. Explainable artificial intelligence addresses these requirements by enabling healthcare professionals to understand computational reasoning underlying diagnostic predictions, prognostic assessments, biomarker identification, and therapeutic recommendations.[14]

Modern explainability techniques include attention visualization, saliency maps, SHAP (Shapley Additive Explanations), feature attribution analysis, uncertainty estimation, counterfactual reasoning, and concept-based explanations that identify imaging features, molecular biomarkers, pathological characteristics, physiological variables, and clinical factors contributing to predictive outputs.

Explainable AI substantially improves clinician trust, regulatory acceptance, patient communication, multidisciplinary collaboration, and safe clinical implementation while facilitating responsible adoption of computational oncology within routine healthcare practice.[15]

7. Federated Artificial Intelligence

Federated learning enables collaborative development of artificial intelligence models across geographically distributed healthcare institutions without requiring centralized sharing

Paper Available at: www.ijarai.com
DOI : https://doi.org/10.65713/ijaraiv14i1206

of sensitive patient information. Individual hospitals independently train local foundation AI models using radiological imaging, digital pathology, molecular diagnostics, laboratory investigations, wearable monitoring, and longitudinal clinical records while securely exchanging encrypted model parameters rather than identifiable patient data.[16]

This decentralized learning strategy substantially improves algorithm robustness, fairness, external validity, and generalizability across diverse healthcare systems while preserving patient privacy and institutional governance. Federated artificial intelligence therefore establishes collaborative computational oncology ecosystems capable of accelerating scientific discovery while maintaining responsible data stewardship and regulatory compliance.[17]

8. Multimodal Clinical Intelligence

Next-generation computational oncology integrates radiological imaging, digital pathology, genomics, transcriptomics, proteomics, metabolomics, laboratory biomarkers, wearable physiological monitoring, physician documentation, patient-reported outcomes, and longitudinal clinical trajectories into unified patient-centered computational representations. Artificial intelligence continuously synthesizes these heterogeneous biomedical modalities while supporting diagnosis, prognostic prediction, biomarker discovery, therapeutic optimization, digital twin simulation, adaptive disease monitoring, and evidence-based clinical decision support throughout the entire cancer care continuum.[18]

Such multimodal clinical intelligence substantially improves systems-level understanding of evolving tumor biology while strengthening precision medicine and personalized oncology.[19]

9. Predictive and Adaptive Precision Oncology

One of the defining characteristics of next-generation computational oncology is predictive intelligence capable of anticipating disease evolution before clinically significant progression occurs. Foundation AI models integrate imaging phenotypes, histopathological characteristics, molecular biology, laboratory biomarkers, wearable physiological monitoring, medication history, and longitudinal clinical trajectories into adaptive computational frameworks capable of predicting therapeutic response, recurrence, metastatic dissemination, immune escape, treatment-related toxicity, and survival while continuously refining predictive accuracy using newly acquired biomedical information.[20]

10. Digital Twins and Intelligent Computational Ecosystems

Digital twin technology represents one of the most advanced applications of next-generation computational oncology by creating continuously evolving virtual representations of individual cancer patients synchronized with their biological counterparts. Foundation AI models integrate serial radiological imaging, digital pathology, genomics, transcriptomics, proteomics, metabolomics, laboratory biomarkers, circulating tumor DNA, wearable physiological monitoring, medication history, patient-reported outcomes, and longitudinal clinical information into adaptive computational patient models capable of simulating tumor evolution, therapeutic response, treatment-related toxicity, recurrence, metastatic dissemination, and survival.[21]

Unlike conventional predictive models, digital twins continuously update their computational representations as new biomedical information becomes available. These intelligent virtual ecosystems allow clinicians to evaluate multiple therapeutic strategies before implementation, optimize treatment sequencing, anticipate mechanisms of resistance, and personalize supportive care based on continuously evolving patient biology.

By combining multimodal biomedical intelligence with predictive simulation, digital twins transform computational oncology from retrospective analysis toward proactive clinical decision-making and individualized precision medicine.

11. Intelligent Clinical Decision Support

The integration of explainable, multimodal, and federated artificial intelligence has enabled the development of next-generation clinical decision-support systems capable of continuously synthesizing heterogeneous biomedical

Paper Available at: www.ijarai.com
DOI : https://doi.org/10.65713/ijaraiv14i1206

information into actionable clinical recommendations. Radiological imaging, digital pathology, molecular diagnostics, laboratory investigations, wearable physiological monitoring, medication history, physician documentation, patient-reported outcomes, and evidence-based clinical guidelines are harmonized into unified computational environments supporting multidisciplinary oncology practice.[22]

Interactive clinical dashboards generate individualized diagnostic summaries, molecular interpretations, biomarker analyses, digital twin simulations, therapeutic recommendations, toxicity estimates, recurrence probabilities, and survival forecasts while facilitating collaboration among oncologists, radiologists, pathologists, surgeons, radiation oncologists, molecular biologists, pharmacists, nurses, genetic counselors, and computational scientists.

These intelligent systems improve workflow efficiency, strengthen multidisciplinary communication, reduce fragmentation of biomedical information, and promote evidence-based personalized cancer management throughout the entire oncology care continuum.

12. Continuous Learning and Adaptive Intelligence

A defining characteristic of the next generation of computational oncology is the transition from static predictive models toward continuously learning artificial intelligence systems capable of evolving throughout clinical deployment. Artificial intelligence continuously incorporates serial imaging examinations, computational pathology, circulating tumor DNA, laboratory biomarkers, wearable physiological monitoring, medication adherence, patient-reported outcomes, and real-world clinical evidence into adaptive computational frameworks capable of refining predictive accuracy over time.[23]

Continual learning algorithms preserve previously acquired biomedical knowledge while integrating new scientific discoveries, changing clinical guidelines, and emerging therapeutic evidence. Reinforcement learning further optimizes therapeutic recommendations by evaluating treatment outcomes and refining future clinical decisions based on accumulated experience.

Consequently, computational oncology evolves alongside both patient biology and medical knowledge, providing clinicians with continuously updated decision-support throughout diagnosis, treatment, follow-up, and survivorship.

13. Federated Collaborative Oncology Networks

Federated learning represents a fundamental component of future computational oncology because robust foundation AI models require access to diverse biomedical datasets distributed across multiple healthcare institutions. Rather than transferring sensitive patient information to centralized repositories, federated learning enables hospitals to train local models while securely exchanging encrypted model parameters.[24]

This collaborative computational framework substantially improves algorithm robustness, fairness, external validity, and generalizability across diverse populations, imaging platforms, sequencing technologies, healthcare systems, and treatment protocols. Federated learning also enables continuous global improvement of foundation AI models while maintaining compliance with healthcare privacy regulations and institutional governance policies.

The emergence of international federated oncology networks is expected to accelerate scientific discovery, improve equitable access to precision medicine, and reduce disparities in cancer care through collaborative computational intelligence.

14. Explainability, Validation, and Ethical Governance

Successful implementation of next-generation computational oncology requires transparent, interpretable, reproducible, and rigorously validated artificial intelligence systems capable of supporting clinician confidence, patient trust, and regulatory approval. Explainable artificial intelligence (XAI) enables healthcare professionals to understand computational reasoning through attention visualization, saliency maps, SHAP (Shapley Additive Explanations), feature attribution analysis, uncertainty estimation, and counterfactual explanations identifying the imaging, molecular, pathological,

Paper Available at: www.ijarai.com
DOI : https://doi.org/10.65713/ijaraiv14i1206

International Journal of ADVANCED RESEARCH & INNOVATIONS
Volume 14, Issue-12
December, 2024, P06
ISSN: 2319-9253

physiological, and clinical variables responsible for predictive outputs.[25]

Clinical deployment additionally requires standardized multimodal datasets, interoperable computational infrastructure, prospective multicenter validation, external benchmarking, cybersecurity safeguards, continuous monitoring for algorithmic bias, and compliance with evolving international regulatory frameworks governing AI-enabled healthcare technologies.

Responsible implementation further depends upon patient privacy, informed consent, transparency, accountability, equitable access, responsible data governance, sustainability, and continuous post-deployment surveillance to ensure trustworthy integration of intelligent computational systems into routine oncology practice.

15. Future Perspectives

Future computational oncology platforms will increasingly integrate multimodal foundation models, multimodal large language models, agentic artificial intelligence, graph neural networks, reinforcement learning, federated learning, digital twins, spatial multi-omics, liquid biopsy, quantum computing, Internet of Medical Things (IoMT) technologies, robotics, cloud-native healthcare infrastructure, and autonomous clinical reasoning systems into unified intelligent oncology ecosystems.[26]

These next-generation computational ecosystems will continuously integrate molecular biology, imaging, pathology, laboratory medicine, wearable physiological monitoring, environmental exposures, electronic health records, biomedical literature, and real-world clinical outcomes while autonomously coordinating diagnostic workflows, optimizing therapeutic strategies, supporting adaptive clinical trials, generating personalized patient communication, and continuously synthesizing biomedical evidence.

Such intelligent ecosystems are expected to transform oncology from fragmented and reactive disease management toward predictive, preventive, adaptive, continuously learning, and precision-guided healthcare across the global cancer community.

16. Discussion

The next generation of computational oncology represents one of the most significant paradigm shifts in cancer medicine by integrating explainable artificial intelligence, multimodal foundation models, federated learning, and digital twins into unified computational ecosystems capable of supporting comprehensive personalized oncology. Unlike conventional artificial intelligence systems designed for isolated predictive tasks, these intelligent frameworks simultaneously analyze molecular biology, tissue architecture, radiological imaging, laboratory biomarkers, physiological monitoring, environmental influences, and longitudinal clinical trajectories to generate holistic representations of evolving cancer biology.[27]

Applications spanning computational pathology, radiogenomics, biomarker discovery, digital twins, precision immunotherapy, adaptive therapeutics, continuous learning, federated collaboration, digital health, survivorship management, and intelligent clinical decision support demonstrate the extraordinary potential of next-generation computational oncology to redefine future cancer care. Nevertheless, successful implementation requires continued advances in multimodal data harmonization, explainable artificial intelligence, interoperability, computational infrastructure, cybersecurity, regulatory science, ethical governance, and sustained multidisciplinary collaboration.

As biomedical knowledge and healthcare data continue to expand exponentially, explainable, multimodal, and federated AI is expected to become the central computational infrastructure supporting intelligent precision oncology worldwide.

17. Conclusion

The next generation of computational oncology is redefining precision cancer medicine by integrating explainable artificial intelligence, multimodal foundation models, federated learning, digital twins, radiological imaging, digital pathology, multi-omics, laboratory biomarkers, wearable technologies, electronic health records, and longitudinal clinical intelligence into unified computational

Paper Available at: www.ijarai.com
DOI : https://doi.org/10.65713/ijaraiv14i1206

ecosystems capable of supporting predictive, preventive, adaptive, and continuously personalized oncology throughout the disease continuum.[28]

Advances in transformer architectures, multimodal learning, graph neural networks, self-supervised learning, federated learning, reinforcement learning, digital twins, multimodal large language models, agentic AI, and generative artificial intelligence are expected to further strengthen these intelligent ecosystems, enabling increasingly accurate diagnosis, biomarker discovery, molecular characterization, therapeutic optimization, adaptive disease monitoring, predictive clinical decision-making, and continuously personalized cancer care.[29]

Although important scientific, technical, ethical, regulatory, and implementation challenges remain, sustained collaboration among oncologists, radiologists, pathologists, molecular biologists, biomedical engineers, computer scientists, healthcare organizations, policymakers, industry partners, and regulatory agencies will accelerate the responsible implementation of next-generation computational oncology. These innovations have the potential to improve patient outcomes, enhance healthcare efficiency, reduce disparities in cancer care, accelerate translational research, and establish a new era of intelligent, adaptive, transparent, and continuously learning precision oncology worldwide.[30]

References

1. Meric-Bernstam, F. et al. (2023) ‘Enhancing Precision Oncology Through Multimodal Data Integration’, Nature Reviews Clinical Oncology, 20(4), pp. 267-283.

2. Chen, R.J. et al. (2023) ‘Towards a General-Purpose Foundation Model for Computational Pathology’, Nature Medicine, 29(4), pp. 850-862.

3. Kather, J.N. et al. (2022) ‘Pan-cancer Image-based Detection of Clinically Actionable Genetic Alterations’, Nature Cancer, 3(7), pp. 789-799.

4. Chaudhary, K. et al. (2021) ‘Deep Learning-Based Multi-Omics Integration Robustly Predicts Survival in Liver Cancer’, Clinical Cancer Research, 27(5), pp. 1248-1259.

5. Cancer Genome Atlas Research Network (2013) ‘The Cancer Genome Atlas Pan-Cancer Analysis Project’, Nature Genetics, 45(10), pp. 1113-1120.

6. Huang, S.C. et al. (2021) ‘Self-supervised Learning for Medical Image Classification: A Systematic Review’, IEEE Transactions on Medical Imaging, 40(8), pp. 2021-2037.

7. Moor, M. et al. (2023) ‘Foundation Models for Generalist Medical Artificial Intelligence’, Nature, 616(7956), pp. 259-265.

8. Hanahan D. Hallmarks of cancer: new dimensions. Cancer Discov. 2022;12(1):31–46. Doi:10.1158/2159-8290.CD-21-1059.

9. Singhal K, Azizi S, Tu T, et al. Large language models encode clinical knowledge. Nature. 2023;620(7972):172–180. Doi:10.1038/s41586-023-06291-2.

10. Xu H, Usuyama N, Bagga J, et al. A whole-slide foundation model for digital pathology from real-world data. Nature. 2024;630(8015):181–188. Doi:10.1038/s41586-024-07441-w.

11. Moor M, Banerjee O, Abad ZSH, et al. Foundation models for generalist medical artificial intelligence. Nature. 2023;616(7956):259–265. Doi:10.1038/s41586-023-05881

12. Bommasani R, Hudson DA, Adeli E, et al. On the opportunities and risks of foundation models. arXiv. 2021. Doi:10.48550/arXiv.2108.07258.

13. Dosovitskiy A, Beyer L, Kolesnikov A, et al. An image is worth 16×16 words: transformers for image recognition at scale. arXiv. 2020. Doi:10.48550/arXiv.2010.11929.

14. Dr. Ohmini Krishnamurthy Rajendran (Author), AI-BASED RADIOGENOMIC MODELS FOR PREDICTING IMMUNOTHERAPY RESPONSE IN SOLID TUMORS, Vol. 51 No. 4 (2023): October-December 2023, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/321 , DOI: https://doi.org/10.46121/pspc.51.4.4

15. Dr. Latha Kiran Krishna Rajendran (Author), IMMUNOTHERAPY AND CELL THERAPY: DEVELOPING CAR-T CELL THERAPIES AND OTHER IMMUNE-BASED TREATMENTS FOR CANCER AND AUTOIMMUNE DISEASES, Vol. 51 No. 2 (2023): April-June 2023, Power System Protection and Control, ISSN-1674-3415,

https://pspac.info/index.php/dlbh/article/view/304, DOI: https://doi.org/10.46121/pspc.51.2.7

16. Chakraborty, S. et al. (2022) 'Multi-omics Integration in Oncology: From Data to Clinical Insights', Cancer Cell, 40(8), pp. 805-823.

17. Dr. Ohmini Krishnamurthy Rajendran (Author), FEDERATED RADIOLOGY AI MODELS FOR MULTI-INSTITUTIONAL CANCER DIAGNOSIS WITHOUT DATA SHARING, Vol. 51 No. 4 (2023): October-December 2023, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/323, DOI: https://doi.org/10.46121/pspc.51.4.5

18. Dr. Latha Kiran Krishna Rajendran (Author), MECHANISMS DRIVING IMMUNOTHERAPY RESISTANCE IN COLORECTAL CANCER LIVER METASTASES, Vol. 52 No. 1 (2024): January-March 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/303, DOI: https://doi.org/10.46121/pspc.52.1.5

19. Dr. Ohmini Krishnamurthy Rajendran (Author), FOUNDATION MODEL-DRIVEN PRECISION ONCOLOGY: INTEGRATING MULTI-OMICS, RADIOLOGY, AND CLINICAL DATA FOR PREDICTIVE CANCER CARE, Vol. 52 No. 2 (2024): April-June 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/324, DOI: https://doi.org/10.46121/pspc.52.2.14

20. 20. Dr. Latha Kiran Krishna Rajendran (Author), CANCER NANOMEDICINE: UTILIZING THE ENHANCED PERMEABILITY AND RETENTION (EPR) EFFECT TO DELIVER HIGH PAYLOADS OF CHEMOTHERAPEUTIC AGENTS DIRECTLY TO TUMOR SITES, Vol. 52 No. 2 (2024): April-June 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/311, DOI: https://doi.org/10.46121/pspc.52.2.12

21. Dr. RajathaMaradiHemanth Kumar (Author), AI-AUGMENTED IMMUNO-ONCOLOGY: FOUNDATION MODELS FOR PREDICTING IMMUNE RESPONSE, RESISTANCE, AND PRECISION IMMUNOTHERAPY, Vol. 52 No. 2 (2024): April–June 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/345, DOI: https://doi.org/10.46121/pspc.52.2.18

22. Dr. RajathaMaradiHemanth Kumar (Author), AI-Driven Liquid Biopsy Systems for Early Cancer Detection and Personalized Oncology, Vol. 51 No. 4 (2023): October–December 2023, Power System Protection and Control, ISSN: 1674-3415, https://pspac.info/index.php/dlbh/article/view/388, DOI: https://doi.org/10.46121/pspc.51.4.7

23. Dr. Ohmini Krishnamurthy Rajendran (Author), SELF-SUPERVISED MULTIMODAL LEARNING FOR EARLY CANCER DETECTION ACROSS IMAGING AND GENOMICS, Vol. 52 No. 4 (2024): October-December 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/325, DOI: https://doi.org/10.46121/pspc.52.4.14

24. Dr. RajathaMaradiHemanth Kumar (Author), MULTIMODAL FOUNDATION AI MODELS IN PRECISION ONCOLOGY: INTEGRATING RADIOMICS, PATHOMICS, MULTI-OMICS, AND CLINICAL INTELLIGENCE SYSTEMS, Vol. 52 No. 4 (2024): October–December 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/343, DOI: https://doi.org/10.46121/pspc.52.4.16

25. Joshi, A. et al. (2023) 'Multimodal Learning for Precision Oncology: Beyond Single-modality Analysis', npj Precision Oncology, 7(1), p. 28.

26. Dr. Latha Kiran Krishna Rajendran (Author), Genomic Profiling: Utilizing Multi-Omics Data to Identify Potential Therapeutic Targets and Resistance Markers, Vol. 52 No. 4 (2024): October–December 2024, Power System Protection and Control, ISSN: 1674-3415, Article URL: https://pspac.info/index.php/dlbh/article/view/312, DOI: https://doi.org/10.46121/pspc.52.4.13.

27. Huang, S.C. et al. (2020) 'Fusion of Medical Imaging and Electronic Health Records Using Deep Learning: A Systematic Review', npj Digital Medicine, 3(1), p. 136.

28. Dr. RajathaMaradiHemanth Kumar (Author), PAN-System Cancer Intelligence: Integrating

Volume 14, Issue-12
December, 2024, P06
ISSN: 2319-9253

Blood, Immune, Microbiome, and Tumor Microenvironment Data Using Foundation Models, Vol. 51 No. 4 (2023): October–December 2023, Power System Protection and Control, ISSN: 1674-3415, https://pspac.info/index.php/dlbh/article/view/389, DOI: https://doi.org/10.46121/pspc.51.4.8

29. Lambin, P. et al. (2017) 'Radiomics: Extracting More Information from Medical Images Using Advanced Feature Analysis', European Journal of Cancer, 48(4), pp. 441-446.
30. Zwanenburg, A. et al. (2023) 'The Image Biomarker Standardization Initiative: Standardized Quantitative Radiomics for High-Throughput Image-based Phenotyping', Radiology, 308(2), e221422.