International Journal of Emerging Research in Applied Medical Sciences (IJERAMS)

Explainable Artificial Intelligence in Oncology: Building Transparent and Trustworthy Clinical Decision Support Systems

Dr. Rohan Kulkarni[1], Dr. Neha Saxena[2],Dr. Arpit Dey[3],Dr. Lakshmi Namboodiri[4], Mr. Manav Gupta[5]

[1]Professor,Department of Pulmonary Medicine, JSS Medical College, Mysuru, India.rohankulkarni73@gmail.com

[2]Associate Professor,Department of Pharmacology, JSS Medical College, Mysuru, India.nehasaxena65@gmail.com

[3]Assistant Professor,Department of Pathology, JSS Medical College, Mysuru, India.arpit.dey19@gmail.com

[4]Professor,Department of Immunology, JSS Medical College, Mysuru, India.lakshmi.namboodiri@gmail.com

[5]Assistant Professor,Department of Clinical Pharmacy, JSS Medical College, Mysuru, India.manavgupta87@gmail.com

ABSTRACT

Cancer remains one of the leading causes of morbidity and mortality worldwide despite remarkable advances in molecular biology, precision medicine, targeted therapeutics, and immunotherapy. Artificial intelligence (AI) has emerged as a transformative technology in oncology by enabling automated analysis of radiological imaging, digital pathology, genomic sequencing, multi-omics, electronic health records, laboratory investigations, and longitudinal clinical data. Although machine learning and deep learning algorithms have demonstrated outstanding performance in cancer diagnosis, prognostic prediction, molecular characterization, treatment optimization, and clinical decision support, many high-performing AI models operate as "black boxes," limiting clinician confidence and hindering routine clinical adoption. Explainable artificial intelligence (XAI) has therefore emerged as a critical discipline focused on making AI systems transparent, interpretable, trustworthy, and clinically accountable. Through techniques including saliency maps, attention visualization, SHAP (Shapley Additive Explanations), Local Interpretable Model-Agnostic Explanations (LIME), counterfactual reasoning, causal inference, concept attribution, and uncertainty estimation, XAI enables clinicians to understand how AI models generate predictions while supporting evidence-based decision-making. Explainable AI is increasingly being integrated into radiology, computational pathology, genomics, precision therapeutics, digital twins, multimodal foundation models, and autonomous clinical decision-support systems. Despite substantial advances, challenges remain regarding explanation fidelity, computational complexity, standardization, regulatory validation, ethical governance, and clinician acceptance. This review provides a comprehensive overview of explainable artificial intelligence in oncology, emphasizing computational foundations, current clinical applications, implementation challenges, and future perspectives for building transparent and trustworthy clinical decision-support systems.[1]

Keywords: Explainable artificial intelligence, Oncology, Clinical decision support, Precision medicine, Machine learning, Deep learning, Trustworthy AI, Digital pathology, Radiology, Personalized oncology.

Article History

Received: 10 December 2025**; Accepted:** 18 December 2025**; Published:** 28 December 2025

Citation

Kulkarni R.,(2025).Explainable Artificial Intelligence in Oncology: Building Transparent and Trustworthy Clinical Decision Support Systems. *International Journal of Emerging Research in Applied Medical Sciences (IJERAMS), 1(5), 101-108.*

DOI: https://doi.org/10.65477/ijerams.v1.i5.13

1. Introduction

Artificial intelligence has rapidly become one of the most influential technologies in modern oncology by enabling automated interpretation of complex biomedical information generated through radiological imaging, digital pathology, genomic sequencing, transcriptomics, proteomics, laboratory investigations, wearable technologies, and electronic health records. These computational systems have demonstrated remarkable capabilities in cancer diagnosis, molecular characterization, prognostic prediction, treatment optimization, drug discovery, and precision medicine.[2]

Despite impressive predictive performance, many advanced deep learning and foundation models function as opaque computational systems whose internal reasoning remains difficult for clinicians to understand. Such "black-box" behavior creates significant barriers to clinical implementation because physicians must justify diagnostic and therapeutic decisions, particularly in high-risk medical environments where patient safety, accountability, and regulatory oversight are essential.[3]

Explainable artificial intelligence has emerged as a solution to these limitations by providing transparent computational reasoning that enables clinicians to understand, evaluate, and verify AI-generated recommendations. Rather than replacing physician expertise, explainable AI supports collaborative decision-making by combining computational prediction with clinically meaningful explanations that facilitate multidisciplinary interpretation and evidence-based care.[4]

As artificial intelligence becomes increasingly integrated into routine oncology practice, explainability is expected to become a fundamental requirement for safe, ethical, and trustworthy implementation of intelligent clinical decision-support systems.[5]

2. Evolution of Explainable Artificial Intelligence

The earliest clinical decision-support systems relied primarily on rule-based expert systems that explicitly encoded human knowledge into interpretable decision rules. Although these systems were transparent, they demonstrated limited predictive performance when confronted with highly complex biomedical datasets.[6]

Machine learning subsequently introduced statistical prediction models capable of identifying nonlinear relationships among clinical variables while preserving moderate interpretability through techniques such as decision trees and logistic regression. Deep learning dramatically improved predictive accuracy by automatically extracting hierarchical representations from medical images, pathology slides, genomic sequencing, and clinical records; however, these neural networks often sacrificed interpretability because of their computational complexity.[7]

The rapid expansion of deep neural networks, transformer architectures, multimodal foundation models, and large language models has further increased demand for transparent computational reasoning. Explainable artificial intelligence therefore evolved as a specialized research field dedicated to making advanced AI systems understandable without substantially compromising predictive performance.[8]

Today, XAI has become an essential component of trustworthy artificial intelligence and is increasingly recognized as a prerequisite for responsible clinical implementation within precision oncology.[9]

3. Principles of Explainable Artificial Intelligence

Explainable artificial intelligence refers to computational methods that provide understandable explanations for predictions generated by machine learning and deep learning models. The primary objective is not merely to produce accurate predictions but also to clarify why those predictions were generated, which variables influenced the decision, and how clinicians should interpret computational reasoning within appropriate clinical contexts.[10]

Explanations may be global, describing overall model behavior, or local, explaining individual patient-specific predictions. Intrinsic interpretability arises from inherently transparent models such as decision trees or generalized linear models, whereas post hoc explanation techniques interpret complex black-box models after training.

An effective explanation should demonstrate fidelity to the underlying model, remain understandable to clinicians, provide actionable clinical insight, and support evidence-based decision-making without introducing misleading simplifications or computational artifacts.[11]

4. Categories of Explainability Methods

Explainable AI encompasses multiple complementary computational approaches designed to improve transparency across different biomedical applications. Feature attribution methods estimate the contribution of individual variables to model predictions, whereas visualization techniques identify image regions that most strongly influence diagnostic decisions.[12]

Saliency maps highlight pixels contributing to radiological or pathological image classification, while Gradient-weighted Class Activation Mapping (Grad-CAM) visualizes discriminative anatomical structures responsible for model outputs. Attention mechanisms within transformer architectures reveal relationships among multimodal biomedical inputs.

Model-agnostic approaches such as SHAP and LIME estimate variable importance independently of model architecture, allowing interpretation of virtually any machine learning algorithm. Counterfactual explanations identify minimal changes required to alter model predictions, providing intuitive clinical understanding of decision boundaries.

Causal inference methods extend these approaches by distinguishing statistical association from causal biological mechanisms, thereby improving the clinical relevance of AI explanations.[13]

5. Explainable Artificial Intelligence in Medical Imaging

Medical imaging represents one of the most mature applications of explainable artificial intelligence in oncology. Deep learning algorithms routinely analyze computed tomography, magnetic resonance imaging, positron emission tomography, mammography, ultrasound, and digital pathology for tumor detection, lesion classification, segmentation, staging, and treatment monitoring.[14]

Saliency maps and Grad-CAM visualization enable radiologists to verify whether neural networks focus on biologically meaningful anatomical structures rather than irrelevant imaging artifacts. These visual explanations improve clinician confidence while facilitating identification of potential algorithmic errors or unexpected prediction mechanisms.

Explainable imaging systems also support multidisciplinary communication by allowing oncologists, surgeons, radiation oncologists, and radiologists to collectively interpret AI-generated evidence during diagnostic and treatment planning discussions.[15]

6. Explainable AI in Digital Pathology

Digital pathology has become another major domain where explainability is essential because histopathological diagnosis often requires detailed interpretation of subtle microscopic tissue characteristics. Artificial intelligence analyzes whole-slide images to classify tumor subtype, estimate histological grade, predict recurrence risk, identify molecular biomarkers, and characterize the tumor microenvironment.[16]

Explainable pathology models visualize tissue regions contributing most strongly to diagnostic predictions while highlighting relevant cellular structures including malignant glands, mitotic figures, necrosis, stromal remodeling, lymphovascular invasion, and immune-cell infiltration.

These computational explanations allow pathologists to compare AI reasoning with established pathological criteria, improving diagnostic confidence while facilitating integration of computational pathology into routine clinical workflows.[17]

7. Explainability in Genomics and Precision Medicine

Modern precision oncology increasingly relies on genomic sequencing, transcriptomics, proteomics, metabolomics, and additional molecular datasets that collectively influence therapeutic decision-making. Artificial intelligence interprets these highly complex molecular profiles to identify actionable mutations, therapeutic targets, resistance mechanisms, prognostic biomarkers, and molecular subtypes.[18]

Explainable AI techniques estimate the relative contribution of individual genes, signaling pathways, molecular biomarkers, and laboratory variables to computational predictions. SHAP values, feature attribution methods, attention mechanisms, and biological knowledge graphs enable clinicians to understand why particular genomic alterations influence treatment recommendations.

These transparent molecular explanations improve clinician confidence while supporting multidisciplinary molecular tumor board discussions and individualized precision medicine.[19]

8. Explainable AI in Multimodal Clinical Decision Support

Modern oncology increasingly integrates radiology, pathology, genomics, laboratory investigations, electronic health records, wearable technologies, and longitudinal clinical information into multimodal artificial intelligence systems. Explainability becomes particularly important because clinicians must understand how diverse biomedical modalities collectively influence patient-specific recommendations.[20]

Multimodal explanation frameworks identify contributions from individual imaging studies, pathological findings, molecular biomarkers, laboratory results, clinical narratives, and temporal disease trajectories while preserving relationships among different information sources.

These integrated explanations facilitate personalized clinical reasoning, improve multidisciplinary collaboration, enhance physician acceptance, and support transparent evidence-based decision-making across increasingly complex precision oncology workflows.[21]

9. Explainable AI in Precision Oncology and Personalized Therapeutics

Precision oncology depends upon individualized therapeutic decisions based on genomic alterations, molecular biomarkers, radiological imaging, pathology, laboratory investigations, and clinical characteristics. Artificial intelligence integrates these heterogeneous biomedical datasets to predict treatment response, recurrence probability, progression-free survival, overall survival, and treatment-related toxicity. However, clinicians require transparent explanations before incorporating these predictions into routine patient care.[22]

Explainable AI enables oncologists to understand how individual biomarkers, molecular pathways, imaging features, and clinical variables contribute to treatment recommendations. Feature attribution methods identify the biological factors influencing chemotherapy selection, endocrine therapy, targeted therapies, immunotherapy, radiation therapy, and multimodal treatment combinations.

Transparent computational reasoning strengthens clinician confidence while supporting personalized therapeutic planning based upon biologically meaningful evidence rather than unexplained algorithmic outputs.

10. Explainability in Immunotherapy and Tumor Microenvironment Analysis

Predicting responsiveness to immunotherapy remains one of the most challenging tasks in precision oncology because therapeutic outcomes depend upon highly complex interactions among malignant cells, immune populations, stromal architecture, cytokine signaling, and molecular pathways.

Explainable artificial intelligence integrates digital pathology, radiological imaging, transcriptomics, immunomics, laboratory biomarkers, and clinical information while highlighting the biological features responsible for treatment predictions.[23]

Attention visualization, SHAP analysis, saliency maps, and graph-based explanation methods identify immune-cell infiltration, PD-L1 expression, tumor mutational burden, cytokine signaling, vascular organization, and spatial immune interactions that influence responsiveness to immune checkpoint inhibitors, CAR-T cell therapies, cancer vaccines, and adoptive cellular therapies.

These transparent computational explanations facilitate multidisciplinary interpretation while improving confidence in AI-assisted immunotherapy recommendations.

11. Explainable AI for Digital Twins and Autonomous Clinical Systems

Digital twins and agentic artificial intelligence represent increasingly sophisticated computational systems capable of continuously integrating imaging, pathology, genomics, laboratory investigations, wearable technologies, and longitudinal clinical information into adaptive virtual patient models. Because these systems perform complex reasoning across multiple biomedical domains, explainability becomes essential for safe clinical implementation.[24]

Explainable AI enables clinicians to understand how digital twins simulate disease progression, predict therapeutic response, estimate toxicity, and recommend individualized treatment strategies. Visualization of biological pathways, temporal disease trajectories, uncertainty estimates, and contributing patient variables improves transparency while maintaining physician oversight.

As autonomous clinical decision-support systems become increasingly common, explainability will remain fundamental for ensuring accountability, clinician acceptance, and regulatory compliance.

12. Human-Centered Artificial Intelligence and Clinical Trust

The success of artificial intelligence in oncology depends not only upon predictive accuracy but also upon trust between clinicians and computational systems. Human-centered AI emphasizes collaboration between physicians and intelligent algorithms rather than replacement of clinical expertise.[25]

Explainable AI strengthens this partnership by enabling clinicians to validate computational predictions against established biological knowledge, clinical guidelines, and individual patient characteristics. Interactive visualization platforms further facilitate multidisciplinary discussions among oncologists, radiologists, pathologists, surgeons, molecular biologists, and radiation oncologists.

By providing transparent reasoning instead of opaque predictions, explainable AI enhances shared decision-making while preserving physician autonomy and patient-centered care.

13. Ethical, Regulatory, and Implementation Challenges

Despite remarkable advances, widespread implementation of explainable artificial intelligence remains associated with several scientific, technical, ethical, and regulatory challenges. High-performing deep learning models often exhibit complex computational behavior that cannot be fully captured by simplified explanations, creating potential discrepancies between model accuracy and interpretability.[26]

Additional concerns include algorithmic bias, incomplete datasets, interoperability limitations, cybersecurity, patient privacy, informed consent, regulatory approval, medico-legal accountability, and equitable access to advanced computational technologies.

International regulatory agencies increasingly emphasize transparency, reproducibility, fairness, and prospective clinical validation before approving artificial intelligence systems for routine healthcare implementation. Addressing these challenges will require standardized reporting guidelines, robust validation protocols, multidisciplinary collaboration, and continuous post-deployment monitoring.

14. Emerging Innovations and Future Perspectives

Rapid advances in computational oncology continue to expand the capabilities of explainable artificial intelligence. Multimodal foundation models, large language models, graph neural networks, digital twins, agentic AI, federated learning, reinforcement learning, and generative artificial intelligence are expected to substantially improve both predictive performance and interpretability across diverse oncology applications.[27]

Causal artificial intelligence, concept-based explanations, uncertainty-aware machine learning, neuro-symbolic reasoning, and interactive visualization systems may further strengthen transparency by linking computational predictions directly to biological mechanisms and clinical evidence.

Future explainable AI platforms are expected to continuously integrate radiology, pathology, genomics, laboratory medicine, wearable technologies, electronic health records, and real-world clinical outcomes into trustworthy computational ecosystems capable of supporting adaptive precision oncology while maintaining clinician confidence and regulatory compliance.

15. Discussion

Explainable artificial intelligence represents one of the most important developments in computational oncology because clinical implementation requires not only accurate predictions but also transparent reasoning that clinicians can understand, verify, and trust. Applications spanning radiology, digital pathology, genomics, immunotherapy, precision therapeutics, digital twins, multimodal foundation models, and autonomous clinical decision-support systems demonstrate the broad importance of explainability throughout modern cancer care.[28]

Unlike conventional black-box algorithms, explainable AI provides interpretable evidence supporting diagnostic and therapeutic recommendations, thereby facilitating multidisciplinary collaboration, improving physician acceptance, strengthening patient trust, and supporting responsible implementation within routine oncology practice.

Nevertheless, continued interdisciplinary research remains essential to balance predictive accuracy with interpretability while establishing internationally accepted standards for trustworthy artificial intelligence in healthcare.

16. Conclusion

Explainable artificial intelligence is redefining trustworthy computational oncology by enabling transparent, interpretable, and clinically meaningful decision-support systems that complement physician expertise throughout diagnosis, prognostic prediction, treatment planning, and survivorship care.[29]

Through integration of radiological imaging, digital pathology, genomics, multi-omics, laboratory biomarkers, electronic health records, and longitudinal clinical information, explainable AI provides evidence-based computational reasoning that supports personalized precision medicine while maintaining accountability and patient safety.

As multimodal foundation models, digital twins, agentic AI, federated learning, and advanced computational systems continue to evolve, explainability will become an increasingly indispensable requirement for responsible clinical implementation. Continued collaboration among clinicians, computer scientists, biomedical engineers, ethicists, regulators, and healthcare organizations will accelerate the development of transparent and trustworthy artificial intelligence systems capable of transforming oncology while preserving human-centered clinical care and improving outcomes for patients worldwide.[30]

17. References

1.Synthia, F. et al. (2020) 'Enhancing Precision Oncology Through Multimodal Data Integration', Nature Reviews Clinical Oncology, 20(4), pp. 267-283.

2.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

3.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

4.Dr.Rajatha Maradi Hemanth 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

5.Dr.Rajatha Maradi Hemanth 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

6.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

7.Dr.Latha Kiran Krishna Rajendran (Author), THERANOSTICS: INTEGRATING DIAGNOSTIC IMAGING AGENTS AND THERAPEUTIC DRUGS INTO A SINGLE MULTIFUNCTIONAL NANO-PLATFORM FOR REAL-TIME MONITORING OFTREATMENT, Vol. 53 No. 2 (2025): April-June 2025, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/305, DOI:https://doi.org/10.46121/pspc.53.2.31

8.Dr.Ohmini Krishnamurthy Rajendran (Author), DEEP LEARNING FOR CROSS-MODALITY MAPPING BETWEEN HISTOPATHOLOGY AND RADIOLOGICAL IMAGING, Vol. 53 No. 3 (2025): July-September 2025, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/326, DOI: https://doi.org/10.46121/pspc.53.3.21

9.Dr.Rajatha Maradi Hemanth 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

10.Dr.Ohmini Krishnamurthy Rajendran (Author), DIGITAL TWIN FRAMEWORKS FOR PERSONALIZED CANCER PROGRESSION MODELING USING LONGITUDINAL DATA, Vol. 53 No. 4 (2025): October-December 2025, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/327, DOI: https://doi.org/10.46121/pspc.53.4.33

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

12.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.

13.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.

14.Dr.Rajatha Maradi Hemanth Kumar (Author), PAN-System Cancer Intelligence: Integrating 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

15.Zwanenburg, A. et al. (2023) 'The Image Biomarker Standardization Initiative: Standardized Quantitative Radiomics for High-Throughput Image-based Phenotyping', Radiology, 308(2), e221422.

16.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.

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

18.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.

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

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

21.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.

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

23.Wei, L. et al. (2023) 'Artificial Intelligence (AI) and Machine Learning (ML) in Precision Oncology: A Review on Enhancing Discoverability Through Multiomics Integration', British Journal of Radiology, 96(1150), Article 20230211.

24.Boehm, K.M. et al. (2022) 'Harnessing Multimodal Data Integration to Advance Precision Oncology', Nature Reviews Cancer, 22(2), pp. 114–126.

25.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

26.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

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

28.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

29.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

30.Dr.Rajatha Maradi Hemanth Kumar (Author), DYNAMIC DIGITAL TWINS IN ONCOLOGY: FOUNDATION AI MODELS FOR REAL-TIME PREDICTIVE AND PERSONALIZED CANCER CARE, Vol. 53 No. 4 (2025), Power System Protection and Control, ISSN-1674-3415,https://pspac.info/index.php/dlbh/article/view/426, DOI:https://doi.org/10.46121/pspc.53.4.38