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CANCER INTELLIGENCE NETWORKS: FEDERATED FOUNDATION MODELS FOR SECURE AND COLLABORATIVE PRECISION ONCOLOGY

[#1]**Dr. Aparna Krishnan,** Professor, Department of Radiation Oncology,
Dr. V. M. Government Medical College, Solapur, India
Aparnakrishnan87@gmail.com

Abstract: Cancer intelligence networks are emerging as a transformative paradigm in precision oncology by combining federated foundation artificial intelligence (AI) models, distributed biomedical intelligence, and privacy-preserving computational infrastructures to enable secure collaboration across healthcare institutions. Conventional AI development in oncology is frequently constrained by fragmented biomedical datasets, institutional data silos, regulatory restrictions, patient privacy concerns, and limited generalizability of locally trained algorithms. Recent advances in foundation AI models, multimodal transformer architectures, graph neural networks, self-supervised learning, federated learning, reinforcement learning, and generative artificial intelligence have enabled decentralized integration of radiological imaging, digital pathology, genomics, transcriptomics, proteomics, metabolomics, epigenomics, spatial biology, laboratory biomarkers, circulating tumor DNA, wearable physiological monitoring, electronic health records, biomedical literature, and longitudinal clinical outcomes without direct exchange of sensitive patient information. These intelligent systems support precision diagnosis, biomarker discovery, prognostic prediction, therapeutic optimization, digital twin simulation, adaptive clinical trials, knowledge graph construction, and evidence-based clinical decision support while preserving institutional autonomy and patient confidentiality. Emerging technologies including multimodal large language models, agentic AI, retrieval-augmented generation, explainable artificial intelligence, cloud-native healthcare platforms, differential privacy, secure multi-party computation, and digital health ecosystems further strengthen collaborative precision oncology by enabling trustworthy, transparent, and continuously adaptive biomedical intelligence. Despite remarkable technological progress, important scientific, technical, ethical, regulatory, and implementation challenges remain regarding interoperability, computational scalability, cybersecurity, model harmonization, governance, fairness, and equitable deployment. This review provides a comprehensive overview of cancer intelligence networks, emphasizing federated foundation models for secure and collaborative precision oncology.[1]

Keywords: *Federated learning, Foundation models, Cancer intelligence networks, Precision oncology, Artificial intelligence, Computational oncology, Digital pathology, Radiomics, Privacy-preserving AI, Personalized medicine.*

1. Introduction

Cancer is a biologically heterogeneous disease characterized by continuous genomic evolution, epigenetic remodeling, immune adaptation, metabolic reprogramming, angiogenesis, stromal remodeling, and dynamic interactions among malignant cells, immune populations, extracellular matrix, vascular structures, and host physiology. These interconnected biological processes evolve throughout diagnosis, treatment, recurrence, metastasis, and survivorship, requiring computational systems capable of integrating heterogeneous biomedical information across diverse healthcare environments.[2]

Modern oncology generates enormous quantities of biomedical information through radiological imaging, digital pathology, genomic sequencing, transcriptomics, proteomics, metabolomics, epigenomics, spatial biology, laboratory investigations, circulating tumor DNA, wearable physiological monitoring, physician documentation, electronic health records, biomedical literature, and patient-reported outcomes. However, these datasets frequently remain isolated within individual healthcare institutions because of regulatory, technical, and privacy constraints, thereby limiting development of robust, generalizable artificial intelligence.[3]

Cancer intelligence networks address these limitations by enabling secure, decentralized collaboration among healthcare institutions through federated foundation models capable of learning from distributed multimodal biomedical information without exchanging identifiable patient data.

2. Evolution of Federated Artificial Intelligence in Oncology

Artificial intelligence in oncology has evolved from institution-specific computational models toward globally collaborative intelligence ecosystems capable of integrating biomedical information across multiple healthcare systems. Early machine learning algorithms were typically developed using single-center datasets, frequently resulting in limited generalizability, algorithmic bias, and reduced clinical applicability across diverse patient populations.[4]

Deep learning substantially expanded computational capabilities through automated feature learning from radiological imaging, digital pathology, genomics, and electronic health records. However, centralized training approaches continued to require large aggregated datasets, creating challenges related to patient privacy, institutional governance, and regulatory compliance.

Federated learning, multimodal foundation models, graph neural networks, and self-supervised learning have subsequently enabled decentralized collaborative training, allowing institutions to jointly develop intelligent oncology models while preserving local data ownership and privacy.[5]

3. Principles of Federated Foundation Models

Federated foundation models differ fundamentally from conventional centralized artificial intelligence because computational learning occurs across distributed institutions without direct transfer of patient-level biomedical data. Rather than aggregating raw datasets into centralized repositories, participating institutions independently train local foundation models while securely exchanging encrypted model parameters that collectively improve generalized biomedical representations.[6]

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, epigenomics, laboratory biomarkers, wearable physiological monitoring, physician documentation, patient-reported outcomes, biomedical literature, and longitudinal clinical trajectories within unified computational embedding spaces.

Graph neural networks further characterize interactions among genes, proteins, signaling pathways, immune populations, imaging phenotypes, tissue architecture, therapeutic targets, physiological variables, environmental exposures, and clinical outcomes, enabling systems-level reasoning across globally distributed oncology datasets.[7]

4. Computational Architecture

Modern cancer intelligence networks consist of interconnected computational layers responsible for local biomedical data acquisition, preprocessing, multimodal representation learning, federated optimization, secure parameter aggregation, graph reasoning, predictive analytics, digital twin simulation, knowledge integration, and intelligent clinical decision support.[8]

The acquisition layer continuously integrates radiological imaging, digital pathology, genomic sequencing, transcriptomics, proteomics, metabolomics, epigenomics, spatial biology, laboratory investigations, circulating tumor DNA, wearable physiological monitoring, physician documentation, biomedical literature, pharmacological databases, clinical guidelines, and electronic health records. Advanced preprocessing pipelines normalize imaging studies, harmonize molecular datasets, encode biomedical narratives using natural language processing, synchronize temporal patient information, and continuously incorporate emerging scientific evidence.

Foundation AI models subsequently generate generalized multimodal embeddings representing molecular biology, tissue architecture, imaging phenotypes, physiological function, environmental exposures, and longitudinal clinical trajectories while secure federated optimization continuously improves global model performance across participating institutions.[9]

5. Federated Precision Diagnosis

One of the most important applications of cancer intelligence networks is precision diagnosis through collaborative learning from distributed multimodal biomedical information. Foundation AI models integrate radiological imaging, digital pathology, molecular biomarkers, laboratory investigations, genomic alterations, physician documentation, biomedical literature, and clinical guidelines while preserving institutional privacy.[10]

Federated learning enables diverse healthcare institutions to collectively improve diagnostic algorithms without exposing sensitive patient information. Models trained across heterogeneous populations demonstrate improved robustness, reduced algorithmic bias, enhanced external validity, and superior diagnostic generalizability compared with institution-specific algorithms.

These collaborative computational approaches substantially improve diagnostic accuracy, molecular classification, biomarker interpretation, and equitable precision oncology.[11]

6. Collaborative Biomarker Discovery

Cancer intelligence networks substantially accelerate biomarker discovery by integrating distributed molecular biology, imaging phenotypes, histopathological architecture, laboratory biomarkers, and clinical outcomes from geographically diverse healthcare institutions. Foundation AI models harmonize genomics, transcriptomics, proteomics, metabolomics, epigenomics, spatial biology, radiomics, and pathomics using multimodal transformers and graph neural networks capable of generating generalized biological representations.[12]

Collaborative learning identifies latent biological relationships among genes, proteins, signaling pathways, immune responses, imaging phenotypes, and therapeutic targets while preserving institutional data sovereignty. Continuous aggregation of distributed biomedical knowledge substantially improves biomarker validation and reproducibility across diverse patient populations.

These computational advances accelerate translational research and precision therapeutic development.[13]

7. Digital Pathology, Radiology, and Multi-Omics Integration

Comprehensive cancer intelligence requires seamless integration of radiological imaging, digital pathology, genomics, transcriptomics, proteomics, metabolomics, epigenomics, immunomics, microbiomics, spatial biology, laboratory biomarkers, and longitudinal clinical outcomes. Foundation AI models harmonize these diverse biomedical modalities using multimodal transformers and graph neural networks capable of generating generalized biological representations of evolving tumor ecosystems.[14]

Artificial intelligence identifies latent relationships among imaging phenotypes, tissue architecture, molecular alterations, immune responses, physiological adaptation, and therapeutic outcomes while continuously learning across federated institutional networks.

These integrated multimodal representations substantially improve biomarker discovery, molecular classification, therapeutic selection, precision immunotherapy, adaptive therapeutics, and translational oncology.[15]

8. Privacy-Preserving Collaborative Intelligence

Privacy preservation represents one of the defining strengths of cancer intelligence networks. Federated learning enables collaborative model development through decentralized optimization, while differential privacy, secure multi-party computation, homomorphic encryption, trusted execution environments, and blockchain-inspired audit mechanisms strengthen protection of sensitive biomedical information.[16]

These privacy-preserving technologies enable institutions to participate in collaborative precision oncology while maintaining regulatory compliance, institutional governance, and patient confidentiality. Simultaneously, explainable

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artificial intelligence improves transparency, clinician trust, and accountability within distributed computational ecosystems.

Such secure collaborative infrastructures establish the technological foundation for trustworthy international precision oncology networks.[17]

9. Intelligent Federated Oncology Ecosystems

One of the greatest strengths of cancer intelligence networks is their ability to unify radiology, pathology, multi-omics, laboratory biomarkers, biomedical literature, pharmacological knowledge, wearable physiological monitoring, electronic health records, patient-reported outcomes, and longitudinal clinical trajectories into distributed yet collaboratively learned computational representations. Rather than relying upon isolated institutional datasets, federated foundation models continuously synthesize multimodal biomedical intelligence across geographically distributed healthcare systems while preserving patient privacy and institutional autonomy. These generalized computational representations establish the foundation for collaborative biomarker discovery, digital twins, intelligent clinical decision support, adaptive therapeutics, equitable artificial intelligence, and continuously learning precision oncology across the global cancer community.[18][19][20]

10. Digital Twins within Cancer Intelligence Networks

Digital twin technology represents one of the most transformative applications of cancer intelligence networks by creating continuously evolving virtual representations of individual cancer patients synchronized with their biological counterparts through federated computational infrastructures. Foundation AI models integrate serial radiological imaging, digital pathology, genomics, transcriptomics, proteomics, metabolomics, epigenomics, spatial biology, 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 disease progression, therapeutic response, treatment-related toxicity, recurrence, metastatic dissemination, and survival.[21]

Unlike conventional digital twins developed from isolated institutional datasets, federated digital twins continuously update their computational representations using distributed biomedical intelligence acquired across multiple healthcare organizations without transferring identifiable patient information. Integration of multimodal molecular biology with predictive simulation enables virtual patients to evaluate alternative therapeutic strategies, optimize treatment sequencing, anticipate mechanisms of therapeutic resistance, personalize supportive care, and estimate long-term clinical outcomes according to evolving patient biology.

By combining federated multimodal intelligence with predictive simulation, digital twins transform computational oncology from institution-specific prediction toward globally collaborative precision medicine.

11. Intelligent Clinical Decision Support

Cancer intelligence networks provide the computational infrastructure for next-generation clinical decision-support systems capable of integrating heterogeneous biomedical information into comprehensive patient-centered recommendations across geographically distributed healthcare systems. Rather than independently interpreting radiological imaging, digital pathology, molecular diagnostics, laboratory investigations, physician documentation, patient-reported outcomes, biomedical literature, and evidence-based clinical guidelines, federated foundation AI models synthesize diverse biomedical information into unified computational representations supporting multidisciplinary oncology practice.[22]

Interactive clinical dashboards generate individualized diagnostic summaries, molecular biomarker analyses, radiomic and pathomic interpretations, digital twin simulations, therapeutic recommendations, toxicity estimates, recurrence probabilities, disease progression forecasts, survival predictions, and longitudinal treatment response assessments while facilitating collaboration among oncologists, radiologists, pathologists, surgeons, radiation oncologists, molecular biologists, pharmacists, nurses, genetic counselors, biomedical engineers, computational scientists, and translational researchers.

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These intelligent systems improve workflow efficiency, strengthen multidisciplinary communication, reduce fragmentation of biomedical information, and promote evidence-based personalized cancer management while maintaining privacy-preserving collaboration.

12. Continuous Learning Across Federated Networks

A defining characteristic of cancer intelligence networks is the ability to continuously evolve as new biomedical information becomes available across participating institutions. Artificial intelligence incorporates serial imaging examinations, computational pathology, circulating tumor DNA, laboratory biomarkers, wearable physiological monitoring, medication adherence, patient-reported outcomes, biomedical literature, pharmacological evidence, clinical guidelines, and real-world treatment outcomes into adaptive federated computational frameworks capable of continuously refining predictive accuracy throughout the patient's clinical journey.[23]

Continual learning algorithms enable incremental refinement of computational knowledge without catastrophic forgetting, while reinforcement learning optimizes diagnostic reasoning, therapeutic prioritization, disease monitoring, toxicity prediction, and supportive care through iterative evaluation of longitudinal patient outcomes. Federated aggregation enables local discoveries to strengthen globally shared foundation models without compromising patient confidentiality.

This adaptive computational paradigm transforms oncology into a continuously learning international scientific ecosystem capable of rapidly translating biomedical discoveries into personalized clinical practice.

13. Federated Governance and Collaborative Intelligence

Long-term success of cancer intelligence networks depends upon robust governance frameworks that ensure secure collaboration, transparency, interoperability, fairness, and responsible artificial intelligence. Participating institutions contribute locally trained foundation models while maintaining ownership of biomedical data, regulatory compliance, and institutional autonomy. Secure parameter aggregation, differential privacy, homomorphic encryption, trusted execution environments, and distributed audit mechanisms collectively strengthen computational security and accountability.[24]

Collaborative governance additionally requires standardized biomedical ontologies, harmonized data formats, quality assurance protocols, model version control, algorithm monitoring, external validation, and multidisciplinary oversight involving clinicians, computational scientists, regulatory agencies, healthcare administrators, and patient representatives.

Such governance structures establish trustworthy international computational ecosystems capable of supporting collaborative precision oncology while preserving ethical responsibility and institutional independence.

14. Explainability, Validation, and Ethical Governance

Successful implementation of federated foundation AI models requires transparent, interpretable, reproducible, and rigorously validated computational systems capable of supporting clinician confidence, patient trust, institutional accountability, and regulatory approval. Explainable artificial intelligence (XAI) enables clinicians to understand federated computational reasoning through attention visualization, saliency maps, SHAP (Shapley Additive Explanations), feature attribution analysis, uncertainty estimation, confidence calibration, multimodal attention mapping, and counterfactual explanations identifying the imaging, molecular, pathological, physiological, pharmacological, 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, transparent reporting standards, fairness auditing, 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, continuous post-deployment surveillance, clinician education, and multidisciplinary oversight to ensure trustworthy deployment of federated oncology intelligence.

15. Future Perspectives

Future cancer intelligence networks 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, single-cell sequencing, liquid biopsy, quantum computing, Internet of Medical Things (IoMT), cloud-native healthcare infrastructure, biomedical knowledge graphs, retrieval-augmented generation, explainable reasoning systems, and autonomous clinical intelligence into globally distributed precision oncology platforms.[26]

These next-generation computational ecosystems will continuously integrate molecular biology, radiological imaging, digital pathology, laboratory medicine, wearable physiological monitoring, environmental exposures, electronic health records, biomedical literature, pharmacological databases, international clinical guidelines, and real-world clinical outcomes while autonomously coordinating biomarker discovery, adaptive therapeutics, personalized treatment planning, survivorship management, multinational clinical trials, and continuous evidence synthesis.

Such intelligent federated ecosystems are expected to transform oncology from isolated institutional practice toward globally collaborative, predictive, adaptive, continuously learning, and precision-guided cancer medicine.

16. Discussion

Cancer intelligence networks represent one of the most significant paradigm shifts in computational oncology by integrating federated foundation models, radiology, pathology, multi-omics, laboratory biomarkers, biomedical literature, pharmacological knowledge, digital biomarkers, digital twins, and distributed clinical intelligence into secure collaborative computational ecosystems capable of supporting comprehensive personalized cancer care. Unlike conventional centralized artificial intelligence systems that require aggregation of sensitive biomedical data, federated intelligence continuously synthesizes heterogeneous molecular, imaging, pathological, physiological, pharmacological, and clinical information while preserving institutional autonomy and patient privacy.[27]

Applications spanning computational pathology, radiogenomics, biomarker discovery, precision immunotherapy, adaptive therapeutics, digital twins, multinational clinical trials, federated collaboration, digital health, survivorship management, intelligent clinical decision support, and translational research demonstrate the extraordinary potential of cancer intelligence networks to redefine future oncology. Nevertheless, successful implementation requires continued advances in multimodal data harmonization, explainable artificial intelligence, interoperability, computational infrastructure, cybersecurity, regulatory science, ethical governance, clinician education, and sustained international collaboration.

As biomedical knowledge and healthcare data continue to expand exponentially, federated cancer intelligence networks are expected to become one of the foundational computational infrastructures supporting global precision oncology.

17. Conclusion

Cancer intelligence networks are transforming precision oncology by integrating federated foundation AI models with radiological imaging, digital pathology, multi-omics, laboratory biomarkers, biomedical literature, electronic health records, digital biomarkers, digital twins, and longitudinal clinical intelligence into secure collaborative computational ecosystems capable of supporting biomarker discovery, prognostic prediction, therapeutic optimization, adaptive disease monitoring, and personalized cancer treatment across geographically distributed healthcare systems.[28]

Advances in multimodal transformer architectures, graph neural networks, self-supervised learning, federated learning, reinforcement learning, multimodal large language models, explainable artificial intelligence, digital twins, agentic AI, retrieval-augmented generation, and generative artificial

intelligence are expected to further strengthen collaborative oncology ecosystems, enabling increasingly accurate molecular characterization, predictive clinical reasoning, adaptive therapeutics, continuous knowledge synthesis, and equitable precision medicine worldwide.[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, patients, and regulatory agencies will accelerate the responsible implementation of cancer intelligence networks. These innovations have the potential to improve patient outcomes, enhance healthcare efficiency, reduce disparities in cancer care, accelerate translational research, facilitate global scientific collaboration, and establish a new era of secure, adaptive, and continuously learning precision oncology worldwide.[30]

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