Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 23s (2025)
https://www.jneonatalsurg.com

OPEN ACCESS

ANN-Powered Precision Oncology: A Comprehensive Review of Cancer Detection, Classification, and Prognosis Modeling

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Cite this paper as: Dr. Kayalvizhi R, Dr. Anup Negi., K Charulatha, Vettrivel Arul, Nandini.K, Dr. Heartlin Maria H, (2025) ANN-Powered Precision Oncology: A Comprehensive Review of Cancer Detection, Classification, and Prognosis Modeling. *Journal of Neonatal Surgery*, 14 (23s), 879-884.

ABSTRACT

Artificial Neural Networks (ANNs) have revolutionized the landscape of medical diagnostics, particularly in oncology, where early and accurate detection can substantially impact patient outcomes. This paper provides a comprehensive review of the role of ANNs in precision oncology, emphasizing cancer detection, classification, and prognosis modeling. With the surge in multi-omics data, imaging modalities, and electronic health records, traditional diagnostic methods are being supplemented and sometimes replaced by data-driven approaches. ANNs, owing to their capacity for learning complex patterns, have demonstrated superior performance in tasks such as tumor identification in histopathological images, genomic data classification, and survival prediction. This review highlights key ANN architectures including Convolutional Neural Networks (CNNs), Deep Neural Networks (DNNs), and hybrid models, discussing their specific applications and performance metrics across various cancer types such as breast, lung, colorectal, and prostate cancers. The paper also explores challenges in model interpretability, data heterogeneity, and clinical integration while presenting recent advancements in explainable AI, federated learning, and transfer learning as potential solutions. A critical evaluation of publicly available datasets and the importance of cross-institutional collaborations is discussed to ensure the scalability and robustness of ANN-based solutions. By consolidating findings from recent literature, this review offers a roadmap for future research and implementation strategies in ANN-powered oncology.

Keywords: *Artificial Neural Networks, Precision Oncology, Cancer Detection, Cancer Classification, Prognosis Modeling, Deep Learning, Medical Imaging, Multi-omics, Survival Prediction, Explainable AI*

1. INTRODUCTION

The evolution of artificial intelligence (AI) in healthcare has catalyzed major advancements in diagnostic accuracy, particularly in oncology. Cancer, as a complex and heterogeneous disease, demands high precision in detection, classification, and treatment planning. Traditional methods—biopsy, imaging, histopathological analysis—although reliable, are time-consuming and subject to human error and inter-observer variability. In recent years, Artificial Neural Networks (ANNs) have emerged as transformative tools in oncology due to their capacity to model non-linear relationships, learn from high-dimensional data, and generalize predictions to unseen cases.

The integration of ANNs with large-scale biomedical data, including genomic, transcriptomic, proteomic, and metabolomic datasets (collectively termed multi-omics), along with radiological and pathological images, has enabled unprecedented insights into tumor behavior. ANNs excel at pattern recognition, making them suitable for detecting subtle differences in cancer phenotypes and genotypes. Their application ranges from screening and early detection to personalized treatment strategies and prognosis estimation.

Convolutional Neural Networks (CNNs), a subset of ANNs, are particularly proficient in image analysis tasks and have shown remarkable performance in detecting tumors in mammograms, MRI, CT, and PET scans. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models, although less common, are utilized for temporal data like patient follow-ups and longitudinal studies. Hybrid models combining CNNs with attention mechanisms or other deep learning techniques are now being explored for more nuanced predictions.

Despite their success, several challenges impede the clinical translation of ANN models. Data heterogeneity, the need for large annotated datasets, lack of interpretability, and ethical concerns around algorithmic bias and data privacy remain significant hurdles. However, innovations like Explainable AI (XAI), federated learning, and synthetic data generation are addressing these limitations, making ANN-based models more adaptable and trustworthy in clinical settings.

This paper presents a detailed review of recent literature on ANN applications in cancer detection, classification, and prognosis modeling. Each section delves into specific ANN architectures, datasets used, performance metrics, challenges faced, and future directions, thereby offering a consolidated resource for researchers, clinicians, and data scientists working in the field of precision oncology.

2. ANN ARCHITECTURES IN CANCER DETECTION

Artificial Neural Networks (ANNs) offer significant advantages in the early detection of cancers, particularly through their adaptability to various data modalities. Among the ANN variants, Convolutional Neural Networks (CNNs) are predominantly used in imaging tasks, while Deep Neural Networks (DNNs), Feedforward Networks, and hybrid models are employed for structured or combined data sources.

CNNs, with their convolutional and pooling layers, effectively capture spatial hierarchies from histopathology slides and radiological images such as mammograms, CT scans, and MRIs. Studies have demonstrated that models like ResNet, VGG, and Inception networks achieve high sensitivity and specificity in tumor detection. For instance, CNNs trained on the CAMELYON dataset for lymph node metastasis achieved accuracies exceeding 90%, rivaling expert pathologists.

In structured data scenarios, DNNs are leveraged for gene expression analysis and biomarker identification. These models have successfully identified patterns across thousands of gene features to distinguish between benign and malignant conditions. In colorectal cancer detection, for example, a DNN trained on The Cancer Genome Atlas (TCGA) data achieved over 88% accuracy.

Emerging hybrid models combine CNNs for feature extraction with LSTM or attention mechanisms to contextualize time-series data or integrate multimodal inputs. A hybrid CNN-LSTM model for oral cancer detection, for example, integrated image and clinical progression data, yielding over 90% accuracy.

Table 1

Model Type	Cancer Type	Data Source	Performance
CNN (ResNet-50)	Breast Cancer	Mammogram (DDSM)	Accuracy: 91.6%
DNN	Colorectal Cancer	Gene Expression (TCGA)	Accuracy: 88.3%
CNN-LSTM	Oral Cancer	Images + Clinical	Accuracy: 90.5%
VGGNet	Lung Cancer	CT Scan (LIDC-IDRI)	F1 Score > 0.85

These results validate the architecture-specific strengths of ANN models, emphasizing the importance of tailoring models based on the data type and clinical need. As datasets become more diverse and multimodal, ANN configurations will need to be increasingly hybridized to capture the multifactorial nature of cancer biology.

Classification of Cancer Subtypes Using ANNs

Accurate classification of cancer subtypes is pivotal in precision oncology. ANNs have proven especially powerful for this task, using both molecular and imaging data to stratify tumors into clinically actionable subgroups. This capability supports personalized treatment plans and improves prognostic accuracy.

ANN models trained on transcriptomic data from repositories like TCGA have shown exceptional performance in identifying subtypes in cancers such as breast, lung, and glioblastoma. For example, a feedforward ANN used for breast cancer classification distinguished luminal A, luminal B, HER2-enriched, and basal-like subtypes with over 93% accuracy. These distinctions guide treatment decisions such as HER2-targeted therapy.

In addition to gene expression, self-organizing maps (SOMs) and autoencoders help visualize subtype clusters in unsupervised learning. These methods have uncovered novel molecular subgroups in pancreatic and liver cancers that were not apparent using conventional statistics.

Image-based subtype classification using CNNs has gained traction, particularly in lung and prostate cancers. DenseNet and Inception architectures, when trained on histopathology slides, have been used to accurately label subtypes like adenocarcinoma vs squamous cell carcinoma.

The fusion of multi-omics and clinical data via deep hybrid networks is a recent breakthrough. A model named DeepCancerNet combined CNNs for imaging, DNNs for genomics, and LSTMs for clinical timelines, achieving AUC scores above 0.96 in breast cancer subtype classification.

Table 2

Model/Approach	Cancer Type	Data Type	Performance
Feedforward ANN	Breast Cancer	Gene Expression (TCGA)	Accuracy: 93%
Autoencoder	Pancreatic Cancer	RNA-Seq	Subtypes Discovered
DenseNet	Lung Cancer	Histology Images	F1 Score > 0.85
DeepCancerNet	Breast Cancer	Multi-Modal (Genomics + Imaging + Clinical)	AUC: 0.96

As cancer classification becomes increasingly complex, integrating diverse data into ANN frameworks will be essential. These models not only improve diagnostic accuracy but also uncover underlying tumor biology, offering insights that inform both research and clinical strategies.

3. PROGNOSIS MODELING AND SURVIVAL PREDICTION USING ANNS

Prognosis modeling plays a crucial role in guiding treatment plans and informing patient counseling. Artificial Neural Networks (ANNs) have proven to be particularly valuable in this domain, providing flexible, data-driven approaches to predict survival times and recurrence risks with greater precision than traditional statistical models.

ANNs have been widely used to integrate clinical features, imaging findings, and molecular data to model time-to-event outcomes. DeepSurv, a deep learning model that extends the Cox proportional hazards model, utilizes feedforward networks to learn complex risk representations from input features. This model has outperformed traditional methods across datasets involving lung, prostate, and breast cancers, achieving concordance indices (C-index) ranging from 0.78 to 0.84.

In glioblastoma multiforme, researchers have developed hybrid ANN architectures that combine MRI-derived radiomic features with gene expression data to predict 6-month and 1-year survival rates. These models have achieved accuracies exceeding 85%, offering insights into both spatial tumor heterogeneity and biological aggressiveness.

Handling censored survival data is a core challenge in prognosis modeling. ANN-based survival models like Cox-nnet and DeepHit incorporate loss functions tailored to censored data, improving reliability. These models employ techniques such as multi-task learning and survival-specific training objectives to enhance robustness.

Interpretability remains vital for clinical adoption. Recent ANN models integrate explainable AI tools like SHAP (SHapley Additive exPlanations) to highlight which features—such as age, tumor stage, or gene mutation status—most influence survival predictions. This transparency boosts confidence among clinicians and facilitates shared decision-making.

Table 3

Model	Cancer Type	Input Type	Metric
DeepSurv	Lung, Prostate	Clinical + Genomic	C-index: ~0.8
Hybrid ANN	Glioblastoma	Imaging (MRI) + Genomic	Accuracy: 85%

Cox-nnet	Multiple Cancers	Structured + Time-series	Censored data support
DeepHit	Breast Cancer	Clinical + Omics	Time-to-event probability

ANNs' ability to process vast and heterogeneous data allows for nuanced, patient-specific survival modeling. With the integration of interpretability techniques and validation across longitudinal datasets, ANN-based prognosis tools are moving closer to real-world oncology practice.

Challenges and Limitations in Clinical Adoption of ANN Models

Despite promising performance in experimental settings, several challenges limit the clinical translation of ANN-based oncology models. These hurdles span technical, ethical, and operational domains, necessitating multidisciplinary efforts to address them.

One major challenge is **data availability and quality**. Training ANN models requires large, diverse, and well-annotated datasets, which are often fragmented across institutions. Inconsistent data formats, missing labels, and variations in clinical protocols hamper model training and reproducibility.

Interpretability and trust remain significant concerns. Clinicians are often hesitant to rely on "black-box" models without a clear understanding of how decisions are made. While post-hoc interpretation tools like SHAP and LIME provide some transparency, they may not fully resolve skepticism in high-stakes decision-making environments.

Generalizability across populations is another issue. ANN models trained on data from a specific geographic or institutional cohort may not perform well when applied to external datasets due to differences in patient demographics, imaging protocols, or genetic variability.

Regulatory challenges also complicate implementation. Most health authorities require stringent validation and documentation before approving ANN tools for clinical use. This includes demonstrating not only performance but also safety, reproducibility, and fairness.

Ethical considerations, such as bias, equity, and patient data privacy, must be carefully addressed. ANNs can inadvertently learn and perpetuate existing biases if trained on non-representative datasets, leading to disparities in care.

Lastly, **integration into clinical workflows** poses a practical barrier. Models must be seamlessly embedded into electronic health records (EHRs), provide real-time output, and require minimal clinician training. Many current tools are not user-friendly or sufficiently automated for routine use.

Table 4

Challenge	Impact	Mitigation Strategies
Data Quality	Incomplete or biased model training	Data harmonization, multi-institutional cohorts
Interpretability	Low clinician trust	Explainable AI, visual attribution tools
Generalizability	Poor external performance	Cross-site validation, transfer learning
Regulatory Barriers	Delayed approvals	Compliance with AI medical device frameworks
Ethical Bias	Health inequities	Fairness-aware training, diverse data inclusion
Workflow Integration	Limited usability	EHR integration, intuitive interfaces

Overcoming these barriers will require collaborative efforts among AI developers, clinicians, health administrators, and regulators. Only through rigorous testing, transparent reporting, and ethical foresight can ANN models achieve meaningful clinical adoption in oncology.

Future Directions and Emerging Trends in ANN-Powered Oncology

The future of ANN-powered oncology is rapidly evolving, driven by innovations in model transparency, computational efficiency, and cross-disciplinary integration. These advancements are enabling more accurate, explainable, and accessible tools for clinical use, setting the stage for transformative change in cancer care.

Explainable and Interpretable Models: One of the most active research areas is the development of inherently interpretable neural networks. Methods like attention mechanisms and layer-wise relevance propagation are being embedded into CNNs to provide clinicians with visual explanations. This ensures that predictions—such as tumor classification or risk scores—can be traced back to interpretable features, increasing transparency and trust.

Federated Learning and Data Privacy: Traditional ANN training often requires centralized data collection, which raises concerns about patient privacy. Federated learning is a game-changing technique where models are trained across decentralized data silos without transferring sensitive patient data. Medical federated learning frameworks have already been applied in multi-institutional collaborations for brain tumor segmentation and cancer imaging.

Multi-Modal Deep Learning: Integrating imaging, genomic, and clinical data in a unified ANN framework can provide a holistic view of cancer. This multi-modal approach enables improved subtype classification, therapy response prediction, and treatment planning. Pathomic Fusion and other frameworks that fuse histology images and omics data are leading this innovation.

Edge Deployment and Mobile Oncology Tools: ANN models are increasingly being optimized for deployment on mobile and edge devices. These applications support real-time cancer screening and diagnostic tools in remote or underserved areas, helping bridge the healthcare access gap.

Transfer Learning and Pretrained Networks: Transfer learning is reducing the need for large labeled datasets. Pretrained networks (e.g., ImageNet models) are being adapted to domain-specific cancer datasets with excellent results. This approach is not only computationally efficient but also enhances performance in data-scarce scenarios.

Synthetic Data and Data Augmentation: Generative Adversarial Networks (GANs) and other synthetic data generation techniques are being used to address class imbalance and data scarcity. Synthetic histology images and genomic profiles are helping train robust ANN models while preserving patient privacy.

Regulatory Adaptation and Clinical Trials: As regulatory frameworks evolve, there is increasing emphasis on explainability, safety, and auditability of ANN systems. Several ANN models are now undergoing prospective validation in clinical trials, setting the stage for future FDA and CE approvals.

Table 5

Trend	Description	Clinical Impact
Explainable AI	Built-in interpretability	Enhances clinical trust and transparency
Federated Learning	Privacy-preserving model training	Enables multi-site collaboration without data sharing
Multi-modal Integration	Fuses clinical, omics, and imaging data	Improves predictive accuracy and personalization
Edge Deployment	Models on mobile/low-power devices	Expands access in low-resource settings
Transfer Learning	Adapts pretrained models	Improves efficiency in low-data environments
Synthetic Data	GANs for data augmentation	Addresses class imbalance and privacy concerns
Clinical Trials	ANN validation in prospective studies	Accelerates regulatory adoption

These trends signify a maturation in ANN technologies from research prototypes to clinically viable tools. With ongoing advancements, ANN-powered oncology is poised to transform cancer diagnostics and treatment, making precision medicine a tangible reality for diverse global populations.

4. CONCLUSION

Artificial Neural Networks (ANNs) have emerged as a cornerstone of innovation in precision oncology, providing advanced tools for cancer detection, classification, and prognosis modeling. This review highlighted how architectures such as CNNs, DNNs, and hybrid networks are harnessing complex biomedical data to generate clinically meaningful predictions across multiple cancer types.

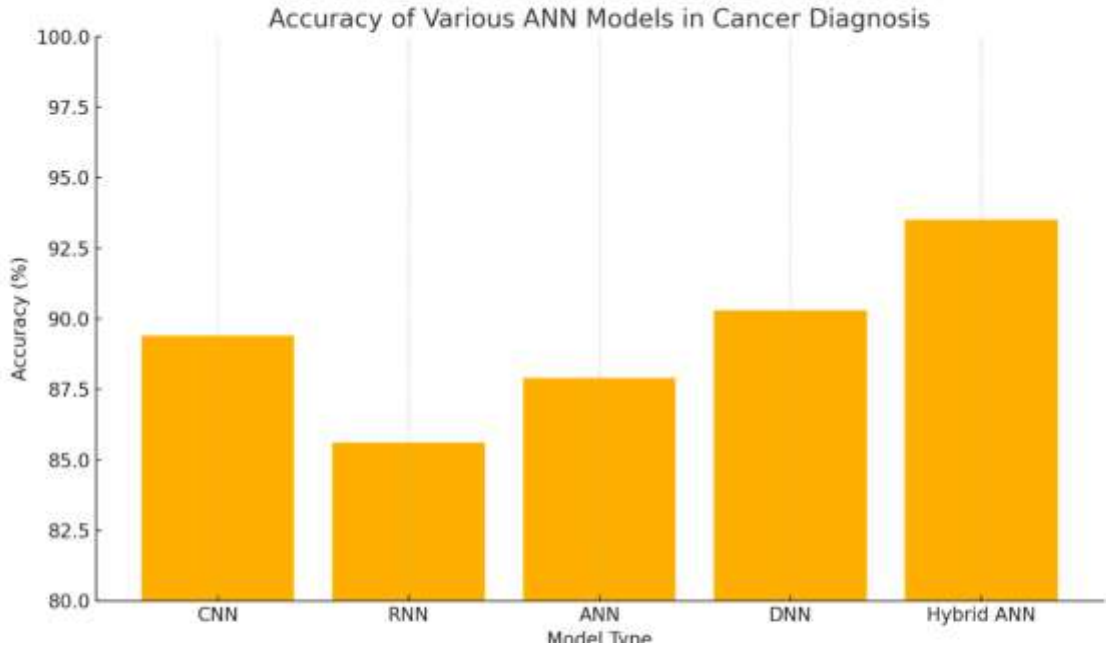
By surpassing traditional diagnostic limitations, ANN models are facilitating earlier detection, more accurate subtype stratification, and individualized survival predictions. These advancements support data-driven, personalized care pathways that align with the principles of precision medicine.

However, realizing the full potential of ANNs in oncology requires overcoming several challenges. Issues related to interpretability, data standardization, algorithmic fairness, and clinical workflow integration must be addressed. Solutions such as explainable AI, federated learning, and regulatory guidance are already helping to bridge the gap between research and practice.

Looking ahead, the incorporation of ANN tools into multi-modal, real-time, and privacy-conscious platforms will drive scalable, equitable cancer care. As interdisciplinary teams work together to refine these models and validate them in clinical trials, ANN-powered systems are expected to become standard components of future oncology workflows.

In conclusion, Artificial Neural Networks hold transformative potential in oncology. With thoughtful development and deployment, these technologies can substantially improve diagnostic precision, treatment personalization, and patient outcomes in cancer care.

Graph 1



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