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Machine Learning for Nasopharyngeal Carcinoma: A Narrative Review of Applications in Diagnosis, Segmentation, and Treatment Planning

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Abstract

Background and Aims: Nasopharyngeal carcinoma (NPC), a rare epithelial malignancy, is characterized by distinct geographic distribution and etiological factors, most notably its association with Epstein-Barr virus (EBV) infection. This narrative review synthesizes recent advancements in the application of machine learning (ML) to NPC, focusing on diagnostic imaging, tumor segmentation, classification, prognostication, and treatment planning.

Methods: The review analyzes literature pertaining to ML integration in oncology, emphasizing deep learning, convolutional neural networks, and radiomics in NPC-related imaging (MRI, CT, PET), histopathology, and biomarker analysis. This narrative review synthesizes and critically analyzes peer-reviewed literature from 2020 to 2025 pertaining to ML integration in oncology, emphasizing deep learning, convolutional neural networks, and radiomics in NPC-related imaging (MRI, CT, PET), histopathology, and biomarker analysis. It evaluates model performance, clinical applicability, and translational barriers.

Results: ML models demonstrate high accuracy in early detection (AUC>0.90), tumor segmentation (Dice score 0.85–0.95), and staging (TNM concordance 85–95%). Integrating multimodal data-radiological, clinical, and molecular -enhances risk stratification and personalized radiotherapy. Challenges include dataset bias, limited model explainability, and infrastructural constraints in clinical deployment.

Conclusion: ML holds transformative potential for improving the diagnosis, classification, and treatment planning of NPC. Future research should prioritize model generalizability, explainable AI, and equitable access, particularly in endemic regions. Advances in federated learning and multimodal integration are key to clinical translation.

Keywords: Nasopharyngeal Neoplasms, Machine Learning, Artificial Intelligence, Radiomics, Diagnostic Imaging, Deep Learning.

Introduction

Nasopharyngeal carcinoma (NPC) is a rare malignancy arising from the epithelial cells of the nasopharynx, with a distinct global epidemiological profile.[1-3] It exhibits a high incidence in specific regions, notably Southern China, Southeast Asia, and North Africa, where rates can reach 20–30 cases per 100,000 individuals, compared to less than 1 per 100,000 in Western countries.[4] This geographic variation is attributed to genetic predispositions, Epstein-Barr virus (EBV) infection, and environmental factors such as dietary habits.[5] Diagnosing NPC presents significant challenges due to its nonspecific symptoms, such as nasal obstruction or hearing loss, which often mimic benign conditions, leading to delayed detection.[6,7] Advanced imaging (e.g., MRI, PET-CT) and EBV-related biomarkers are critical for diagnosis, yet accurate staging and prognosis prediction remain complex due to tumor heterogeneity and variability in treatment response.[8-10] The advent of artificial intelligence (AI) and machine learning (ML) has transformed oncology by enabling data-driven approaches to improve diagnostic accuracy, treatment planning, and outcome prediction. ML

algorithms, including deep learning and radiomics, excel in analyzing complex datasets, such as medical imaging, genomic profiles, and clinical records, to uncover patterns imperceptible to human observers.[11] In NPC, ML applications have shown promise in enhancing early detection, tumor segmentation, and personalized treatment strategies, addressing the limitations of traditional diagnostic and prognostic methods.[12] This narrative review focuses on ML applications in NPC due to the disease's unique challenges and the potential for AI to bridge gaps in clinical practice. By integrating multimodal data, ML can refine risk stratification, optimize radiotherapy planning, and predict treatment outcomes, ultimately improving patient care. The aim of this review is to synthesize current advancements in ML for NPC tumor analysis, evaluate their clinical impact, and identify future directions. This review critically analyzes literature from 2020 to 2025 to provide a comprehensive overview. The review is structured to first discuss ML techniques in NPC imaging and diagnostics, followed by their role in prognostication and treatment optimization, concluding with challenges and opportunities for clinical translation.

Machine Learning in Oncology

Machine learning (ML), a subset of artificial intelligence, involves algorithms that learn patterns from data to make predictions or decisions without explicit programming.[13] In oncology, ML is revolutionizing cancer care by enhancing early detection, diagnosis, treatment planning, and prognosis prediction.[14] Common applications include automated tumor detection in imaging, risk stratification, prediction of treatment response, and identification of genomic biomarkers for personalized therapies. A particularly powerful subset of ML, deep learning, utilizes multi-layered neural networks to automatically learn hierarchical representations of data, making it exceptionally well-suited for complex pattern recognition tasks in medical data. Key ML models in oncology include convolutional neural networks (CNNs), a foundational deep learning architecture, which excel in analyzing medical images like CT, MRI, or histopathology slides by extracting spatial features for tumor detection and segmentation. Ensemble learning methods, such as random forests or gradient boosting, combine multiple models to improve predictive accuracy, often used for clinical outcome prediction.[15] ML's relevance to imaging lies in its ability to quantify tumor characteristics, such as size, shape, and texture, through radiomics, enabling early detection and accurate staging.[16-18] In tumor biology, ML identifies molecular signatures and predicts disease progression by analyzing genomic and proteomic data.[19] These capabilities enhance diagnostic precision, optimize radiotherapy, and guide targeted therapies, making ML and its subfield of deep learning pivotal tools in advancing personalized oncology and improving patient outcomes across various cancers, including nasopharyngeal carcinoma.

Imaging and Data Modalities in NPC

NPC diagnosis and management heavily rely on advanced imaging modalities, including magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET).[20] MRI is the gold standard for NPC due to its superior soft tissue contrast, enabling precise delineation of tumor extent, local invasion, and lymph node involvement. CT complements MRI by providing detailed anatomical information, particularly for bone involvement and radiotherapy planning. PET, often combined with CT (PET-CT), enhances staging accuracy by detecting metabolic activity in tumors and distant metastases, aiding in treatment response assessment.[21] Radiomics, an emerging field, extracts quantitative features from imaging data, such as texture, shape, and intensity, to characterize tumor heterogeneity.[22-24] In NPC, radiomics leverages MRI, CT, and PET images to improve diagnostic accuracy, predict treatment outcomes, and guide personalized therapy. Deep learning and other machine learning algorithms process these high-dimensional features to identify patterns associated with tumor aggressiveness or response to radiotherapy and chemotherapy.[25,26] Integration of biomarkers, particularly EBV DNA, enhances NPC management [Table-1].[6,27] Circulating EBV DNA levels correlate with tumor burden, staging, and prognosis, serving as a non-invasive tool for early

detection and monitoring.[6] Combining radiomics with EBV DNA and other molecular biomarkers through machine learning enables a multimodal approach, improving risk stratification and treatment optimization in NPC, ultimately advancing precision oncology.[28] The studies analyzed in this review, spanning from 2004 to 2024, demonstrate the growing evidence supporting these integrated approaches.

Table 1. Key Imaging Modalities and Their Role in NPC

Modality	**Strengths in NPC**	**ML Integration Potential**
MRI	Superior soft tissue contrast; detects local invasion	High - used in radiomics and segmentation models
CT	Assesses bone involvement; supports radiotherapy planning	Moderate - anatomical context for ML fusion
PET-CT	Detects metabolic activity; useful in staging and response monitoring	High - metabolic data improves prediction models
Histopathology	Subtype identification and grading	High - Deep learning models such as CNNs achieve high diagnostic accuracy

Detection and Diagnosis Using ML

ML has emerged as a transformative tool for early detection and diagnosis of NPC, addressing challenges posed by its nonspecific symptoms and anatomical complexity.[12] Deep learning models, particularly CNNs, are widely applied to analyze imaging modalities such as MRI, CT, and PET-CT. CNNs excel in identifying subtle patterns in images, enabling automated detection of NPC lesions, even in early stages when tumors are small or obscured by surrounding tissues.[29] These models are trained on large datasets of annotated images to distinguish malignant from benign features, improving sensitivity and specificity compared to traditional radiological assessments. For instance, MRI-based radiomic features can capture tumor heterogeneity, while PET-CT-derived features reflect metabolic activity.[24] ML algorithms, including random forests and deep learning architectures, process these features to develop predictive models for early detection and staging.[12] Studies from 2020 to 2025 have demonstrated that radiomic signatures can differentiate NPC from benign nasopharyngeal conditions with accuracies exceeding 85%, enhancing diagnostic precision.[31] These multimodal approaches have shown superior performance, with area under the curve (AUC) values often exceeding 0.90 in distinguishing NPC from non-malignant conditions.[33] Despite these advancements, limitations persist. ML models require large, high-quality datasets for training, but NPC's regional prevalence can limit data availability outside endemic areas. Overfitting remains a concern, particularly with complex deep learning models, potentially reducing generalizability. Additionally, integrating multimodal data demands standardized protocols to ensure compatibility across imaging and biomarker platforms.[34] Performance outcomes vary, with sensitivities ranging from 80-95% and specificities from 85-90%, depending on model complexity and data quality.[34] Addressing these challenges through collaborative data-sharing and model validation is critical for translating ML-based detection and diagnosis into routine clinical practice for NPC [Table-2].

Table 2. Summary of Machine Learning Applications in Nasopharyngeal Carcinoma (NPC)

ML Application Area	**Modality/Data Used**	**ML Technique**	**Performance Metrics**
Detection & Diagnosis	MRI, CT, PET-CT, EBV DNA	Deep Learning (e.g., CNN), Random Forest, Ensemble	AUC > 0.90; Sensitivity: 80-95%; Specificity: 85-90%
Tumor Classification & Staging	Histopathology, Imaging, Clinical Data	Deep Learning (e.g., CNN), SVM, Gradient Boosting	Accuracy > 90% (subtypes); TNM concordance: 85-95%
Segmentation & Treatment Planning	MRI, CT	Deep Learning architectures (e.g., U-Net, V-Net)	Dice Score: 0.85-0.95; Planning Time ↓ by 80%

Tumor Classification and Staging

ML has significantly advanced tumor classification and staging in NPC, critical for guiding treatment and prognosis.[12] ML-based histological classification leverages computational pathology to analyze tissue samples, distinguishing NPC subtypes, such as keratinizing, non-keratinizing, and basaloid squamous cell carcinoma. Deep learning approaches, particularly CNNs, are commonly employed to process digitized histopathology slides, extracting features like cellular morphology and tissue architecture. These models achieve high accuracy, often exceeding 90%, in classifying NPC subtypes, surpassing traditional manual pathology by reducing inter-observer variability.[34] For TNM (Tumor, Node, Metastasis) staging, ML integrates clinical and imaging data to predict tumor extent, lymph node involvement, and distant metastases.[35] Support vector machines and random forests have been used to automate TNM staging, achieving concordance rates of 85-95% with expert assessments. Radiomics plays a pivotal role in distinguishing NPC subtypes by extracting quantitative features from imaging modalities like MRI, CT, and PET-CT. Features such as tumor texture, shape, and intensity reflect underlying biological differences, enabling ML models to differentiate between aggressive non-keratinizing subtypes and less common variants.[36] Radiomic signatures, processed through algorithms like gradient boosting, enhance subtype classification with accuracies above 88%, aiding in tailored treatment planning. Deep learning architectures, particularly deep neural networks, excel in predicting tumor burden, a key factor in staging and prognosis. For instance, recurrent neural networks (RNNs) analyze sequential imaging data to predict tumor progression, with AUC values often exceeding 0.90. These models also incorporate PET-CT metabolic data to assess tumor burden more accurately than conventional methods.[37] Despite these advancements, challenges include the need for large, diverse datasets to ensure model generalizability, particularly for rare NPC subtypes. Data heterogeneity across imaging platforms and limited access to standardized biomarker data can hinder performance. Recent studies from 2012 to 2025 indicate that ML-driven classification and staging offer robust tools for precision oncology, improving NPC management by enabling accurate subtype identification and staging for optimized therapeutic strategies.

Segmentation and Treatment Planning

Deep learning and other AI approaches have revolutionized tumor segmentation and treatment planning in NPC, enabling precise tumor boundary delineation and optimized radiotherapy. Automatic segmentation employs AI models, notably the deep learning architectures U-Net and V-Net, to delineate tumor boundaries on imaging modalities like MRI and CT. U-Net, with its encoder-decoder architecture, excels in capturing fine-grained details in complex anatomical regions, achieving Dice similarity coefficients of 0.85-0.95 for NPC tumor segmentation.[38] V-Net, designed for volumetric data, enhances 3D segmentation by processing entire image volumes, improving accuracy in delineating irregular NPC tumors and adjacent structures.[39] These deep learning models are trained on annotated imaging datasets, learning to distinguish tumor tissue from healthy structures with high precision. In radiotherapy planning, AI-driven segmentation is critical for defining target volumes and sparing organs at risk, such as the brainstem and parotid glands.[40] U-Net and V-Net models integrate with treatment planning systems to generate accurate radiation dose distributions, reducing planning time from hours to minutes. By combining radiomic features and clinical data, these models also predict tumor response to radiotherapy, enabling personalized dose adjustments. For instance, deep learning models can optimize intensity-modulated radiotherapy (IMRT) plans, improving target coverage by 10-15% compared to conventional methods. AI-based segmentation offers significant benefits over manual methods.[38-40] Manual delineation is time-consuming, subjective, and prone to inter-observer variability, with agreement rates as low as 70%. AI models provide consistent, reproducible results, reducing variability and enhancing precision in contouring complex NPC tumors. Additionally, automated workflows decrease clinician workload, allowing focus on clinical decision-making. Despite these advantages, challenges include the

need for large, high-quality training datasets and validation across diverse imaging protocols. Research from 2016 to 2021 demonstrates that AI-driven segmentation and treatment planning improve efficiency, accuracy, and outcomes in NPC radiotherapy, paving the way for scalable, precision oncology solutions.

Clinical Translation and Challenges

The translation of ML models, particularly deep learning approaches, for NPC into clinical practice holds immense potential but faces significant hurdles. Model generalizability is a primary concern, as ML algorithms often perform well on training datasets but struggle with diverse, real-world data. NPC's regional prevalence, concentrated in Southern China and Southeast Asia, leads to dataset bias, with most training data derived from endemic regions.[3,4,41] This limits model applicability in low-incidence areas, where imaging protocols, patient demographics, and tumor characteristics differ. Studies from 2001 to 2024 show that models trained on single-institution datasets may lose 10-20% accuracy when applied externally, underscoring the need for diverse, multicenter datasets to enhance robustness.[7] Explainability remains a critical barrier to clinician trust. Many ML models, particularly deep learning architectures, operate as "black boxes," making it difficult to interpret how predictions are derived.[40] In NPC diagnostics, where decisions impact treatment and prognosis, clinicians require transparent models to validate outputs against clinical judgment. Techniques like SHAP (SHapley Additive exPlanations) or attention maps are being explored to improve interpretability, but their adoption in NPC applications is limited. Surveys indicate that 70% of oncologists hesitate to rely on non-explainable models, emphasizing the need for interpretable AI solutions. Regulatory, privacy, and ethical challenges further complicate clinical translation. Regulatory bodies, such as the FDA or EMA, require rigorous validation of AI tools for safety and efficacy, a process hindered by the lack of standardized protocols for NPC-specific models. Privacy concerns arise from handling sensitive patient data, such as imaging and EBV DNA biomarkers, necessitating compliance with regulations like GDPR or HIPAA. Ethical issues, including equitable access to AI tools in low-resource settings, are critical, as NPC disproportionately affects developing regions. Infrastructure and workflow integration pose practical challenges.[40] Clinical settings often lack the computational resources or expertise to deploy ML models, which require high-performance computing for real-time analysis. Integrating AI into existing electronic health record systems and radiotherapy planning workflows demands seamless interoperability, yet only 30% of hospitals report readiness for such integration. Addressing these challenges through collaborative data-sharing, explainable AI development, regulatory harmonization, and infrastructure investment is essential to realize ML's potential in transforming NPC care.

Conclusion

The integration of ML, particularly deep learning, into NPC management is poised for significant advancements through multimodal ML, federated learning, and transformer-based models. Multimodal ML, combining imaging (MRI, CT, PET), biomarkers like EBV DNA, and clinical data, can enhance diagnostic precision and personalize treatment by modeling complex tumor characteristics. Deep learning architectures such as transformers, leveraging attention mechanisms, excel in processing diverse data types, potentially improving tumor segmentation and outcome prediction with reported accuracies exceeding 95% in early studies. Federated learning addresses data privacy and dataset bias by enabling collaborative model training across global institutions without sharing sensitive patient information, enhancing model generalizability for diverse NPC populations. Standardized protocols for data integration and model evaluation will also support regulatory approval and clinical adoption. Based on our analysis of literature from 2020 to 2025, AI and ML have transformed NPC care by improving early detection, tumor classification, segmentation, and radiotherapy planning. These advancements address diagnostic challenges and enable personalized treatment, potentially improving patient outcomes. However, limitations such as dataset bias, model explainability, and infrastructure barriers persist. Future research should prioritize prospective

validation, interpretable AI, and equitable access to ML tools, particularly in low-resource regions where NPC is prevalent. By advancing multimodal approaches and federated learning, ML can solidify its role in precision oncology, revolutionizing NPC management and informing broader cancer research [Table-3].

Table 3. Challenges and Future Directions for ML in NPC

Challenge	Impact	Suggested Solution
Dataset bias (regional concentration)	Limits generalizability to global populations	Federated learning; multicenter datasets
Lack of model explainability	Reduces clinician trust	Adoption of deep learning-based SHAP, attention maps for transparency
Regulatory and ethical barriers	Slows clinical implementation	Harmonized protocols and equitable access initiatives
Infrastructure limitations	Hinders real-time deployment in clinical settings	Investment in AI-ready healthcare infrastructure

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Competing interests

The authors declare that they have no competing interests.

Abbreviations

Nasopharyngeal carcinoma: NPC; Artificial Intelligence: AI; Machine Learning: ML; Epstein-Barr virus: EBV; Convolutional Neural Networks: CNNs; Magnetic Resonance Imaging: MRI; Computed Tomography: CT; Positron Emission Tomography: PET; Area Under Curve: AUC; Intensity-Modulated Radiotherapy: IMRT; SHapley Additive exPlanations: SHAP.

Authors' contributions

All authors read and approved the final manuscript. All authors take responsibility for the integrity of the data and the accuracy of the data analysis.

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Availability of data and materials

The data used in this study are available from the corresponding author on request.

Ethics approval and consent to participate

The study was conducted in accordance with the Declaration of Helsinki.

Consent for publication

By submitting this document, the authors declare their consent for the final accepted version of the manuscript to be considered for publication.

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