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Recent Advances in DeepLabV3-DenseNet Leveraging Radiomics Feature Extraction and Non-Invasive Detection of Microsatellite Instability in Colorectal Cancer with a Hyperparameters-Tuned Pre-trained Model: A Systematic Review

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Abstract

Microsatellite instability (MSI) is a critical biomarker in colorectal cancer (CRC), influencing prognosis and therapeutic decision-making, particularly for immunotherapy. Traditional MSI detection methods rely on invasive tissue biopsies and molecular testing, which are time-consuming and costly. Recent advances in artificial intelligence (AI), deep learning, and radiomics have enabled non-invasive MSI prediction using medical imaging and histopathological data. This systematic review explores recent developments (2020–2023) in MSI detection using deep learning architectures such as DeepLabV3, dense Net, and hybrid frameworks combined with radiomics feature extraction. Studies demonstrate that convolutional neural networks (CNNs) and transformer-based models can accurately predict MSI status directly from histopathological slides and imaging modalities. For example, deep learning systems have achieved high diagnostic performance with AUROC values exceeding 0.95 in large-scale validation cohorts. Additionally, radiomics-based approaches using CT and PET imaging have shown promising results in non-invasive MSI prediction by extracting high-dimensional quantitative features. Hybrid models integrating feature extraction, segmentation (DeepLabV3), and classification (dense Net) further enhance predictive accuracy by capturing spatial and contextual information. Despite these advancements, challenges such as data heterogeneity, computational complexity, and clinical validation remain. This review provides a comprehensive analysis of methodologies, comparative performance, and future directions for AI-driven MSI detection.

Introduction

Colorectal cancer (CRC) remains a major global health concern, with high mortality rates emphasizing the need for early detection and personalized treatment. Microsatellite instability (MSI), caused by defects in the DNA mismatch repair system, serves as a critical biomarker in CRC. It plays an essential role in determining prognosis and guiding treatment decisions, particularly for immunotherapy, as MSI-high tumors respond more effectively to immune checkpoint inhibitors. However, traditional MSI detection techniques such as PCR and immunohistochemistry are invasive, time-intensive, and require specialized laboratory setups.

To overcome these limitations, artificial intelligence (AI) and medical imaging have emerged as promising alternatives for non-invasive MSI prediction. Deep learning models have demonstrated the ability to predict MSI status directly from histopathological images, reducing reliance on molecular testing. Recent large-scale studies have reported high diagnostic accuracy, with AUROC values reaching up to 0.96, highlighting the potential of AI-driven approaches in clinical settings.

Radiomics further enhances non-invasive cancer diagnostics by extracting quantitative features from imaging modalities such as CT, PET, and MRI. These features capture tumor heterogeneity, texture, and morphology, enabling differentiation between MSI and microsatellite stable tumors. Advanced deep learning architectures like DenseNet and DeepLabV3 contribute significantly to this domain, where segmentation models isolate tumor regions and classification models improve prediction accuracy, forming efficient end-to-end diagnostic frameworks.

Recent innovations, including attention mechanisms, transformer-based models, and graph neural networks, have further improved MSI prediction performance and robustness. Techniques such as self-supervised and multi-instance learning help address data limitations. Despite these advancements, challenges like data heterogeneity, limited labeled datasets, computational demands, and lack of model interpretability continue to hinder clinical adoption. This study reviews current DeepLabV3-DenseNet and radiomics-based approaches, comparing their effectiveness and identifying gaps for future research in non-invasive cancer diagnostics.

Literature Review

The literature on microsatellite instability (MSI) prediction in colorectal cancer (CRC) has rapidly evolved with the integration of artificial intelligence (AI), particularly deep learning and radiomics. Early foundational studies demonstrated that histopathological images contain sufficient morphological information to infer molecular characteristics such as MSI status. For instance, Echle et al. (2020) and Kather et al. (2020) showed that convolutional neural networks (CNNs) trained on large, multi-institutional datasets could achieve high diagnostic accuracy, with AUROC values reaching up to 0.96. These studies established the feasibility of replacing traditional MSI detection methods, such as PCR and immunohistochemistry, with non-invasive, image-based AI models. However, they also highlighted significant limitations, including the need for large annotated datasets, high computational resources, and challenges related to scalability in real-world clinical settings.

Subsequent research focused on improving generalization, efficiency, and reducing dependence on labelled data. Yamashita et al. (2021) introduced MSINet, demonstrating strong performance across validation datasets, although limited dataset size restricted scalability. Similarly, Schirris et al. (2021) proposed the Deep SMILE framework based on self-supervised learning, which reduced reliance on annotated data while maintaining high accuracy. Weakly supervised approaches, such as those by Bilal et al. (2021) and Saillard et al. (2021), leveraged multiple instance learning (MIL) to process whole-slide images without requiring pixel-level annotations, significantly reducing annotation effort. These methods improved practicality but introduced challenges related to interpretability and potential misclassification in heterogeneous tumour regions.

Radiomics-based approaches further expanded the scope of MSI prediction by utilizing quantitative imaging features derived from CT, PET, and MRI scans. Studies by Cao et al. (2021), Lu et al. (2020), and Kim et al. (2023) demonstrated that radiomic features—capturing tumour texture, shape, and heterogeneity—can effectively differentiate MSI-high from microsatellite stable (MSS) tumours. Hybrid models, such as those proposed by Fu et al. (2022) and Zhang et al. (2022), combined deep learning features with handcrafted radiomic descriptors, achieving improved predictive performance. Despite their promise, these approaches face challenges related to feature reproducibility, variability in imaging protocols, and increased model complexity due to the integration of heterogeneous data sources.

Advancements in deep learning architectures have significantly enhanced MSI prediction performance. DenseNet-based models (Shi et al., 2022; Chen et al., 2021) improved feature reuse and gradient flow, while DeepLabV3-based segmentation frameworks (Jiang et al., 2023; Zhang et al., 2023) enabled precise tumour region extraction, enhancing downstream classification accuracy. Attention mechanisms and transformer-based models (Wei et al., 2022; Shao et al., 2023) introduced the ability to capture long-range dependencies and contextual information, outperforming traditional CNNs in several cases. Graph neural networks (Zhou et al., 2023; Wang et al., 2023) further improved performance by modeling spatial relationships within tumour microenvironments. However, these advanced architectures require large datasets, complex training pipelines, and significant computational power, which may limit their widespread adoption.

Recent studies have also emphasized multi-modal learning and model generalization across diverse datasets. Li et al. (2022, 2023) developed frameworks integrating histopathology and radiomics data, demonstrating improved diagnostic accuracy by leveraging complementary information from different modalities. Transfer learning approaches (Kather et al., 2021; Chen et al., 2021) enhanced performance on limited datasets, while pan-cancer models (Kather et al., 2022) demonstrated the scalability of MSI prediction across multiple cancer types. Bias-reduction techniques, such as the XDEEP-MSI framework (Bustos et al., 2021), addressed dataset bias and improved reliability. Validation studies (Echle et al., 2021) further confirmed the robustness of AI-based MSI models across international cohorts. Nevertheless, challenges such as domain adaptation, cross-institution variability, and regulatory barriers continue to hinder clinical implementation.

Hybrid frameworks integrating multiple techniques represent the current state-of-the-art in MSI prediction. Sharma et al. (2023) proposed a comprehensive model combining DeepLabV3 for segmentation, DenseNet for classification, radiomics features, and hyperparameter-optimized pre-trained networks. This integrated approach achieved superior accuracy and generalization, demonstrating the benefits of combining complementary methodologies. However, the increasing complexity of such systems introduces challenges in terms of computational cost, model interpretability, and real-time applicability. Additionally, the requirement for high-quality annotated data for segmentation tasks remains a bottleneck.

Overall, the literature indicates that AI-driven MSI prediction has transitioned from proof-of-concept studies to highly sophisticated, multi-modal frameworks capable of achieving near-clinical accuracy. Deep learning, radiomics, and hybrid approaches have collectively improved the non-invasive detection of MSI, offering significant potential for personalized cancer treatment. However, key challenges persist, including data heterogeneity, limited availability of annotated datasets, computational demands, and lack of interpretability. Addressing these issues will be critical for translating AI-based MSI detection systems into routine clinical practice. Future research should focus on developing lightweight, interpretable, and generalizable models, along with standardized datasets and validation protocols to ensure reliability and clinical acceptance.

ime implementation remained challenges.

Comparative Table

Study	Year	Method	Key Technique	Advantage	Limitation
Echle	2020	DL	CNN	High accuracy	Data heavy
Yamashita	2021	DL	MSINet	Generalizable	Limited data
Kim	2023	Radiomics	PET	Non-invasive	Feature selection
Bustos	2021	DL	XDEEP	Bias reduction	Complex
Schirris	2021	SSL	DeepSMILE	Less labelling	Complexity
Kather	2020	DL	CNN	Robust	Data heavy
Bilal	2021	MIL	Weak supervision	Scalable	Less interpretable
Cao	2021	Radiomics	CT	Non-invasive	Variability
Fu	2022	Hybrid	CNN+Radiomics	Accurate	Complex
Wei	2022	Transformer	Attention	High accuracy	Data heavy
Kather	2021	DL	Transfer learning	Generalizable	Interpretability
Saillard	2021	MIL	Attention	Localization	Complex
Zhang	2022	Hybrid	Radiomics+DL	Improved accuracy	Feature fusion

Shi	2022	DL	DenseNet	Efficient	Overfitting
Jiang	2023	Segmentation	DeepLabV3	Precise ROI	Annotation
Lu	2020	Radiomics	CT	Non-invasive	Reproducibility
Wang	2021	DL	Attention CNN	Accurate	Complex
Chen	2021	DL	DenseNet TL	Efficient	Domain shift
Li	2022	Multi-modal	CT+Histology	High accuracy	Integration
Zhou	2023	GNN	Graph model	Spatial learning	Complex
Coudray	2020	DL	CNN	Genetic prediction	Bias
Echle	2021	DL	CNN	Robust	Validation
Kather	2022	DL	Pan-cancer	Scalable	Variability
Bilal	2022	MIL	Attention	Accurate	Resource heavy
Fu	2022	Hybrid	Radiomics+DL	Accurate	Redundancy
Shao	2023	Transformer	Self-attention	Strong	Data heavy
Wang	2023	GNN	Graph DL	Accurate	Complex
Zhang	2023	Hybrid	DeepLabV3+DenseNet	Best	Annotation
Li	2023	Multi-modal	Fusion	High accuracy	Complex
Sharma	2023	Hybrid	DL+Radiomics	Best performance	High complexity

Comparative Analysis

The comparative analysis reveals that MSI detection methods have evolved from traditional radiomics and machine learning approaches to advanced deep learning and hybrid architectures. Radiomics-based methods offer non-invasive solutions but suffer from reproducibility issues. Deep learning models, particularly CNNs and Denese architectures, provide high accuracy but require large datasets and computational resources. Transformer-based models and graph neural networks further enhance performance by capturing global and spatial dependencies.mHybrid approaches integrating DeepLabV3 for segmentation, Dense Net for classification, and radiomics for feature extraction demonstrate superior performance by combining complementary strengths. However, these models introduce complexity and require careful optimization. Overall, hybrid frameworks represent the most promising direction for future MSI detection systems.

Discussion

Recent advancements in MSI detection using deep learning and radiomics highlight the growing importance of non-invasive diagnostic methods in colorectal cancer. Deep learning models, particularly CNNs, Dense Net, and transformer-based architectures, have demonstrated high accuracy in predicting MSI status from histopathology and imaging data. Radiomics-based approaches complement these models by extracting quantitative features that capture tumour heterogeneity. Hybrid frameworks combining DeepLabV3 segmentation and Dense Net classification further enhance performance by improving feature representation. However, challenges such as data heterogeneity, computational complexity, and lack of interpretability remain significant barriers to clinical adoption. Future research should focus on developing lightweight, explainable, and scalable models. Integration of multi-modal data and advanced optimization techniques can further improve performance and reliability.

Conclusion

The rapid advancement of artificial intelligence (AI) and medical imaging has transformed microsatellite instability (MSI) detection in colorectal cancer, shifting from invasive traditional methods to efficient non-invasive approaches. Radiomics techniques extract quantitative features from imaging data, providing insights into tumour characteristics and offering an alternative to biopsy-based testing, although their performance is limited by variability in imaging protocols and feature extraction. Deep learning models, particularly convolutional neural networks such as DenseNet, have shown superior capability in capturing complex patterns from histopathological images, enabling accurate and automated MSI prediction. The integration of segmentation models like DeepLabV3 further enhances detection by precisely identifying tumour regions and improving feature quality.

Emerging AI techniques, including transformer-based models and graph neural networks, have improved MSI prediction through better contextual and relational learning. Hybrid approaches that combine deep learning, radiomics, and optimization methods achieve the highest performance by leveraging complementary strengths. However, these models face challenges such as high computational demands, large data requirements, and limited interpretability. Future research should focus on developing efficient, scalable, and explainable models, along with integrating multi-modal data and conducting real-world clinical validation. Overall, AI-driven MSI detection represents a promising direction for improving non-invasive diagnosis and personalized treatment in colorectal cancer.

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