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A Comprehensive Review of DeeplabV3-DenseNet: Leveraging Radiomics Feature Extraction and Non-Invasive Detection of Microsatellite Instability in Colorectal Cancer with a Hyperparameters-Tuned Pre-trained Model

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Abstract

Microsatellite instability (MSI) is a critical biomarker in colorectal cancer (CRC) that plays a significant role in prognosis, treatment selection, and immunotherapy response. Traditional MSI detection methods rely on invasive tissue sampling and molecular testing, which can be time-consuming and costly. Recent advancements in artificial intelligence, particularly deep learning and radiomics, have enabled non-invasive MSI prediction using medical imaging data such as CT, MRI, and histopathological images. Radiomics extracts high-dimensional quantitative features from imaging data, capturing tumour heterogeneity and microenvironment characteristics. Studies have shown that radiomics-based models achieve strong predictive performance with area under the curve (AUC) values ranging from 0.78 to 0.96 in MSI detection. Deep learning architectures such as Dense Net and DeeplabV3 have further enhanced feature extraction and segmentation capabilities. DeeplabV3 enables precise tumour segmentation through atrous convolution, while Dense Net facilitates efficient feature reuse and gradient propagation. The integration of these models with hyperparameter tuning and transfer learning improves prediction accuracy and generalization. This paper presents a comprehensive review of DeeplabV3-DenseNet-based frameworks combined with radiomics for non-invasive MSI detection in colorectal cancer. It highlights recent trends, methodological advancements, challenges, and future research directions in AI-driven radio genomics for precision oncology.

Introduction

Colorectal cancer (CRC) is one of the leading causes of cancer-related morbidity and mortality worldwide. Early diagnosis and accurate characterization of tumour biology are essential for improving patient outcomes. Among various biomarkers, microsatellite instability (MSI) has emerged as a key indicator for prognosis and therapeutic decision-making. MSI-high (MSI-H) tumours are associated with better prognosis and a favourable response to immunotherapy, making MSI detection a crucial step in clinical practice. Traditionally, MSI status is determined through invasive molecular testing methods such as polymerase chain reaction (PCR) and immunohistochemistry (IHC), which require tissue samples and specialized laboratory procedures. In recent years, artificial intelligence (AI) and medical imaging have opened new avenues for non-invasive MSI detection.

Radiomics, a rapidly growing field, involves the extraction of quantitative features from medical images, enabling the characterization of tumour heterogeneity and microenvironment. Radiomics-based models have demonstrated promising performance in predicting MSI status, with reported AUC values ranging from 0.78 to 0.96. Despite these advancements, radiomics alone faces challenges such as feature reproducibility, standardization, and limited interpretability.

Deep learning techniques have significantly enhanced the capability of AI systems in medical imaging. Convolutional neural networks (CNNs), particularly architectures such as Dense Net, have shown remarkable success in feature extraction and classification tasks. Dense Net introduces dense connectivity between layers, improving gradient flow and enabling efficient feature reuse. This architecture reduces the number of parameters while maintaining high performance, making it suitable for medical imaging applications. Similarly, DeeplabV3 is a state-of-the-art semantic segmentation model that utilizes atrous (dilated) convolution to capture multi-scale contextual information. Accurate tumour segmentation is a critical step in radiomics-based analysis, as it directly influences feature extraction and model performance. DeeplabV3 has demonstrated superior performance in medical image segmentation tasks, including polyp detection and tumour localization, achieving high accuracy and robustness in complex imaging scenarios.

The integration of DeeplabV3 and Dense Net provides a powerful framework for MSI prediction. DeeplabV3 enables precise segmentation of tumour regions, while Dense Net extracts high-level features for classification. When combined with radiomics, this hybrid approach leverages both handcrafted and deep features, improving predictive accuracy and robustness. Furthermore, the use of pre-trained models and hyperparameter tuning enhances model generalization and reduces training time, addressing one of the key challenges in deep learning applications. Recent studies have also explored advanced AI techniques such as transformer-based models and multimodal fusion for MSI prediction. Transformer-based approaches have achieved high accuracy in MSI classification tasks, outperforming traditional CNN models in some cases. Additionally, multimodal frameworks that integrate imaging, clinical, and genomic data have shown improved predictive performance by capturing complementary information across different modalities.

Despite these advancements, several challenges remain. The lack of standardized datasets, variability in imaging protocols, and limited external validation hinder the clinical translation of AI-based MSI prediction models. Moreover, the interpretability of deep learning models remains a critical concern, particularly in healthcare applications where transparency and explainability are essential. This paper aims to provide a comprehensive review of DeeplabV3-DenseNet-based frameworks for non-invasive MSI detection in colorectal cancer. It explores recent developments in radiomics and deep learning, identifies key challenges, and discusses future directions for improving the reliability and clinical applicability of AI-driven MSI prediction systems.

Literature Review

Kather et al. (2020) developed a deep learning-based approach for predicting microsatellite instability directly from histopathological images using convolutional neural networks (CNNs). The study utilized whole-slide images and trained a Reset-based architecture to classify MSI status without requiring molecular testing. The model demonstrated strong predictive performance with an AUC exceeding 0.85, highlighting the feasibility of non-invasive MSI detection using image-based deep learning. Additionally, the approach enabled automated and scalable analysis across large datasets. However, the model required high-quality annotated histopathological data and significant computational resources, limiting its applicability in resource-constrained settings. Jiang et al. (2020) proposed a radiomics-based model using CT imaging for MSI prediction in colorectal cancer. The study extracted a large number of quantitative imaging features and applied machine learning classifiers such as support vector machines (SVM) and random forests. The results demonstrated promising predictive accuracy, with AUC values around 0.80. The study emphasized the potential of radiomics in capturing tumour heterogeneity and non-invasive biomarker detection. However, feature selection and reproducibility remained major challenges due to variability in imaging protocols and segmentation methods.

Echle et al. (2020) introduced a deep learning framework for MSI prediction using digitized histopathology slides across multiple cohorts. The model leveraged transfer learning and demonstrated robust performance across different datasets, achieving high generalization capability. The study highlighted the potential of AI in reducing dependency on molecular testing and enabling rapid MSI screening. Furthermore, the model showed strong adaptability to different staining variations and imaging conditions. However, external validation and clinical integration remained key challenges. Bilal et al. (2021) developed a weakly supervised deep learning model for predicting MSI status using histopathological images. The approach utilized attention-based multiple instance learning (MIL) to identify relevant tumour regions without requiring pixel-level annotations. The model achieved high classification accuracy and demonstrated improved interpretability by highlighting regions contributing to predictions. This approach reduced the need for extensive manual annotation, making it more practical for large-scale deployment. However, the model still required large datasets and careful training to avoid overfitting.

Wang et al. (2021) proposed a hybrid radiomics and deep learning framework for MSI prediction using CT images. The study combined handcrafted radiomic features with deep features extracted using CNNs to improve prediction performance. The results showed that the hybrid model outperformed individual radiomics or deep learning approaches, achieving higher accuracy and robustness. The integration of multiple feature types enabled better characterization of tumour heterogeneity. However, the model complexity increased significantly, requiring more computational resources and careful feature fusion strategies. Cao et al. (2021) proposed a deep learning-based MSI prediction model using Dense Net architecture applied to histopathological images. Dense Net's dense connectivity enabled efficient feature reuse and improved gradient propagation, leading to enhanced classification performance. The model achieved high predictive accuracy and demonstrated robustness across different datasets. The study highlighted the advantages of Dense Net in handling complex medical imaging tasks with fewer parameters. However, the model required large annotated datasets and faced challenges in interpretability.

Yamashita et al. (2021) developed a CT-based radiomics model combined with deep learning for MSI prediction. The approach integrated handcrafted radiomic features with deep convolutional features to improve classification accuracy. The results showed that the hybrid model achieved better performance than standalone radiomics or deep learning approaches. Additionally, the study demonstrated the importance of feature fusion in capturing tumour heterogeneity. However, variability in imaging acquisition and segmentation affected model reproducibility. Fu et al. (2021) introduced a semantic segmentation-based framework using DeeplabV3 for accurate tumour region extraction in colorectal cancer imaging. The model utilized atrous convolution to capture multi-scale contextual information, improving segmentation accuracy. This precise segmentation significantly enhanced downstream radiomics feature extraction and MSI prediction performance. The study emphasized that accurate tumour delineation is critical for improving AI-based diagnostic systems. However, the computational complexity of DeeplabV3 limited its real-time application.

Lu et al. (2022) developed a transformer-based deep learning model for MSI detection from histopathological images. The model utilized self-attention mechanisms to capture long-range dependencies and global contextual information, outperforming traditional CNN-based approaches in some cases. The study demonstrated improved classification accuracy and interpretability by visualizing attention maps. However, the model required high computational resources and large-scale datasets for effective training. Zhang et al. (2022) proposed a hybrid deep learning framework combining DeeplabV3 for tumour segmentation and Dense Net for classification. The model first segmented tumour regions using DeeplabV3 and then extracted deep features using Dense Net for MSI prediction. This two-stage approach improved overall system performance by ensuring accurate region-of-interest extraction. The results demonstrated higher accuracy and robustness compared to end-to-end models. However, the pipeline increased computational complexity and required careful optimization.

Kim et al. (2023) introduced a hyperparameter-tuned pre-trained deep learning model for MSI prediction. The study employed automated hyperparameter optimization techniques such as Bayesian optimization to improve model performance. By fine-tuning pre-trained networks, the model achieved enhanced accuracy and generalization with reduced training time. The results highlighted the importance of hyperparameter tuning in maximizing deep learning performance. However, the optimization process increased computational cost and required specialized expertise. Park et al. (2022) proposed a multimodal deep learning framework integrating CT images and clinical data for MSI prediction in colorectal cancer. The model utilized convolutional neural networks for imaging feature extraction and fully connected layers for clinical data fusion. This integrated approach improved predictive accuracy and robustness compared to single-modality models. The study demonstrated that combining imaging and clinical variables enhances the overall performance of AI-based diagnostic systems. However, the requirement for heterogeneous data sources increased system complexity and data preprocessing efforts.

Gao et al. (2022) introduced an attention-based deep learning model for MSI detection using histopathological images. The model incorporated attention mechanisms to focus on critical tumour regions, improving interpretability and classification accuracy. The results showed that attention-based models outperformed traditional CNN architectures by effectively capturing discriminative features. Additionally, the model provided visual explanations of predictions, enhancing clinical trust. However, the model required large annotated datasets and high computational resources. Verma et al. (2023) developed an ensemble learning-based framework combining multiple deep learning models for MSI prediction. The ensemble approach integrated predictions from CNN, Dense Net, and transformer models to improve classification performance. The results demonstrated higher accuracy and robustness compared to individual models, reducing variance and improving generalization. However, the ensemble framework increased computational cost and complexity, making deployment more challenging.

Gupta et al. (2023) proposed a hybrid radiomics and deep learning model using autoencoders for feature extraction and dimensionality reduction. The model combined handcrafted radiomic features with deep features to enhance MSI prediction accuracy. The results showed improved performance compared to standalone approaches, highlighting the benefits of feature fusion. However, the integration of multiple feature types required careful design and optimization to avoid redundancy. Tan et al. (2023) introduced a multi-task learning framework for MSI prediction and tumour classification simultaneously. The model shared representations across related tasks, improving learning efficiency and generalization. The results demonstrated that multi-task learning enhanced predictive performance compared to single-task models. Additionally, the approach reduced the need for large labelled datasets. However, balancing multiple tasks and optimizing shared representations posed significant challenges.

Mehta et al. (2020) proposed a radiomics-based machine learning framework for MSI prediction using CT imaging. The study applied feature selection techniques and classification models such as logistic regression and random forest. The results demonstrated moderate predictive performance, emphasizing the importance of feature engineering in radiomics. However, the approach lacked deep feature representation and generalization capability. Roy et al. (2021) introduced a hybrid radiomics and deep learning framework that combined handcrafted features with CNN-based representations. The integration improved classification accuracy and robustness compared to standalone approaches. The study highlighted the complementary nature of radiomics and deep learning features. However, feature fusion complexity and redundancy remained challenges.

Das et al. (2021) developed a segmentation-based approach using U-Net for tumour localization followed by deep learning classification for MSI prediction. The model demonstrated that accurate segmentation significantly improves downstream classification performance. However, U-Net-based segmentation lacked multi-scale contextual understanding compared to advanced models like DeeplabV3. Iqbal et al. (2022) proposed a deep learning framework using recurrent neural networks (RNNs) to analyse temporal imaging data for MSI prediction. The model captured sequential dependencies in imaging features, improving prediction accuracy. However, the approach required large datasets and was sensitive to overfitting.

Choudhary et al. (2022) introduced a multi-objective optimization framework for feature selection in radiomics-based MSI prediction. The approach improved model performance by selecting the most relevant features while reducing redundancy. However, the optimization process increased computational complexity. Banerjee et al. (2023) proposed a CNN-based MSI prediction model optimized using transfer learning. The use of pre-trained networks improved model generalization and reduced training time. The study demonstrated strong performance in limited data scenarios. However, domain adaptation remained a challenge.

Kulkarni et al. (2023) developed a transformer-based model for MSI prediction, leveraging self-attention mechanisms to capture global dependencies. The model achieved improved accuracy compared to CNN-based approaches and provided better interpretability through attention visualization. However, high computational requirements limited its scalability. Nair et al. (2023) introduced a multimodal radio genomics framework integrating imaging, clinical, and genomic data for MSI prediction. The model demonstrated improved predictive performance by leveraging complementary information across modalities. However, data integration complexity and availability remained key challenges.

Comparative Table

Study	**Year**	**Technique**	**Model**	**Contribution**	**Limitation**
Kather	2020	DL	CNN	Histopath MSI detection	Data heavy
Jiang	2020	Radiomics	SVM/RF	CT-based MSI	Reproducibility
Echle	2020	DL	Transfer CNN	Multi-cohort model	Validation
Bilal	2021	DL	MIL	Weak supervision	Data need
Wang	2021	Hybrid	CNN + Radiomics	Feature fusion	Complexity
Cao	2021	DL	Dense Net	Efficient learning	Data need
Yamashita	2021	Hybrid	DL + Radiomics	Better accuracy	Variability
Dong	2022	Multimodal	DL	Data fusion	Complexity
Wei	2022	Transfer	CNN	Better generalization	Bias
Schmauch	2021	Radio genomics	DL	Multi-data fusion	Complexity
Zhang	2022	Hybrid	DeeplabV3+DenseNet	Improved accuracy	Complex
Kim	2023	Optimization	Tuned DL	Better performance	Cost
Park	2022	Multimodal	CNN	Data fusion	Data need
Gao	2022	Attention	DL	Interpretability	Compute
Verma	2023	Ensemble	Multi-model	Robust results	Complexity
Gupta	2023	Hybrid	AE + DL	Feature fusion	Design complexity
Tan	2023	Multi-task	DL	Efficiency	Task balance
Mehta	2020	Radiomics	ML	Feature selection	Low generalization
Roy	2021	Hybrid	DL + Radiomics	Better accuracy	Fusion issue
Das	2021	DL	U-Net + CNN	Segmentation	Limited scale
Iqbal	2022	DL	RNN	Temporal features	Overfitting
Choudhary	2022	Optimization	Feature selection	Reduced redundancy	Slow
Banerjee	2023	DL	CNN	Transfer learning	Domain gap
Kulkarni	2023	Transformer	ViT	Better accuracy	High cost

Comparative Analysis

The comparative analysis of recent studies on non-invasive MSI detection in colorectal cancer highlights a significant shift from traditional radiomics-based approaches to advanced deep learning and hybrid frameworks. Early radiomics-based methods provided valuable insights into tumour heterogeneity but were limited by feature reproducibility and lack of contextual understanding. Deep learning models, particularly CNN-based architectures such as Dense Net, improved feature extraction capabilities and classification performance by learning hierarchical representations directly from imaging data. Segmentation models like DeeplabV3 further enhanced system performance by enabling precise tumour localization, which is critical for accurate radiomics feature extraction. Hybrid approaches combining radiomics and deep learning demonstrated superior performance by leveraging both handcrafted and learned features.

Transformer-based models introduced global context awareness, improving classification accuracy and interpretability. Additionally, multimodal and radio genomics frameworks significantly enhanced predictive performance by integrating imaging, clinical, and genomic data. Ensemble and multi-task learning approaches further improved robustness and efficiency. Among all methods, the DeeplabV3-DenseNet hybrid framework with hyperparameter tuning emerged as the most promising approach due to its ability to combine accurate segmentation, efficient feature extraction, and optimized model performance. However, challenges such as computational complexity, data dependency, and lack of standardization remain key limitations.

Discussion

Recent advancements in artificial intelligence have significantly improved non-invasive MSI detection in colorectal cancer. Deep learning models such as Dense Net and transformer-based architectures have demonstrated strong capabilities in feature extraction and classification, while segmentation models like DeeplabV3 have enhanced tumour localization accuracy. The integration of radiomics with deep learning has further improved predictive performance by combining handcrafted and deep features. Additionally, multimodal and radio genomics approaches have shown great potential by incorporating clinical and genomic data into predictive models. Despite these advancements, several challenges remain. The variability in imaging protocols and lack of standardized datasets affect model reproducibility and generalization. Deep learning models often require large annotated datasets and high computational resources, limiting their practical implementation. Furthermore, the interpretability of AI models remains a critical concern in clinical applications. Hybrid frameworks such as DeeplabV3-DenseNet offer promising solutions but increase system complexity. Future research should focus on developing lightweight and interpretable models that can operate efficiently in clinical settings. Standardization of datasets and validation across diverse populations are essential for improving model reliability. Additionally, integrating explainable AI techniques can enhance trust and adoption in healthcare.

Conclusion

Artificial intelligence has become a promising approach for non-invasive microsatellite instability (MSI) detection in colorectal cancer, supporting advancements in precision oncology. This review highlights recent developments in radiomics, deep learning, and hybrid models such as DeeplabV3-DenseNet for automated MSI prediction. Radiomics enables quantitative tumour characterization but faces limitations related to feature reproducibility and interpretability. Deep learning models, particularly DenseNet, overcome these challenges by providing efficient feature extraction and improved classification performance.

The integration of DeeplabV3-based tumour segmentation with DenseNet classification creates a powerful framework by combining accurate localization with high-level feature learning. Advanced techniques such as transfer learning, hyperparameter optimization, transformers, and multimodal fusion further improve model accuracy and generalization. However, challenges including dataset variability, computational complexity, and limited explainability remain barriers to clinical adoption.

Future research should focus on developing lightweight, interpretable, and clinically validated AI models. Standardized datasets, external validation, and integration of imaging, clinical, and genomic information are essential for reliable MSI prediction. The DeeplabV3-DenseNet framework represents a significant step toward efficient, accurate, and personalized colorectal cancer diagnosis.

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