A Deep Residual Learning-Based Framework for Cancer Metastasis Detection Using Autoencoders and Limited Tumor Data With Whole-Slide Imaging

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Colorectal cancer is the second leading cause of cancer deaths worldwide, with 154,270 cases and 52,900 deaths estimated in 2025. Conventional screening methods, such as imaging scans and blood tests, are costly, time-intensive, and can only diagnose metastasis when the tumor has spread to distant organs and tissues. Past studies using deep learning (DL) for diagnosing colorectal cancer have achieved significant results, but they rely heavily on supervised learning and only a few of them were extended to cover the detection of metastatic signs in the primary tumor site. In this study, I propose a novel two-stage DL framework for tumor localization and detection using semi-supervised learning and unannotated whole-slide images (WSI). First, a ResNet50 was fine-tuned for classification in colorectal WSIs distinguishing tumor (TUM) from normal (NORM) patches. Tumor-classified patches underwent further analysis via a convolutional autoencoder (CAE) to identify metastatic regions based on mean squared error (MSE) as 'anomalies'. High MSE indicates structural deviations in tumor patches, suggesting potential early metastatic features. Macenko’s color normalization ensured stain consistency and hyperparameter tuning optimized model performance. The proposed framework was evaluated on the NCT-CRC-HE-100K dataset, wherein the baseline model (TUM v/s NORM) achieved an exceptional specificity of 98.63% and an AUROC of 0.99, outperforming the current benchmark models. Based on reconstruction frequency trends, the optimal threshold for detecting potential metastasis with the CAE was established at 0.0054 (97th percentile of MSE). A software called CatherNet-0 will be developed to assist pathologists and medical professionals in WSI analysis for colorectal cancer diagnosis.

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