Predicting Patient Suitability for Adaptive Radiotherapy Using CT and Deep Learning

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Introduction

Adaptive radiotherapy (ART) using the Varian Ethos system requires high-quality Cone Beam Computed Tomography (CBCT) images for accurate contouring and treatment plan adaptation. However, CBCT images generally have lower image quality compared to standard simulation CT scans. This is due to their single-rotation acquisition and increased scatter radiation, which leads to reduced soft tissue contrast, particularly in larger patients. Currently, there is no reliable way to predict in advance whether a patient's CBCT quality will be sufficient for Ethos-based adaptive planning before their first treatment session.

In this study, we developed a deep learning-based algorithm to classify patients as suitable (adaptive) or unsuitable (non-adaptive) for Ethos-based treatment based on their simulation CT (Sim CT) data. By identifying patients likely to have poor CBCT quality at the time of simulation, this approach aims to reduce unnecessary treatment delays and optimize clinical workflow.

Methods

A convolutional neural network (CNN) was developed using the MONAI framework to perform binary classification of patient suitability for Ethos-based adaptive radiotherapy. The dataset consisted of simulation CT images from 30 patients: 25 suitable and 5 unsuitable due to poor CBCT quality. Images were preprocessed with resampling and intensity normalization to ensure consistent input to the model, and data augmentation techniques (e.g., rotation, shifting) were used to mitigate overfitting given the small sample size. The model was trained over 10 epochs and designed to output a binary classification: "Suitable for Ethos" or "Not Suitable." Model performance was evaluated using a separate test set containing both suitable and unsuitable cases, which were not included in the training dataset.

Results

On the test set, the model correctly identified 4 out of 5 patients, accurately flagging those patients with CBCT quality was insufficient for accurate contouring. The anticipated clinical workflow is as follows: when a new patient undergoes simulation, their Sim CT data will be processed through the trained model to determine whether they should be scheduled for adaptive radiotherapy workflow or Image-Guided Radiation Therapy (IGRT) workflow. This approach has the potential to prevent unnecessary replanning and minimize treatment delays.

Two representative simulation CT images are shown to the right. Figure 1 depicts a patient classified as suitable for Ethos-based ART, with anticipated high CBCT quality. Figure 2 shows a patient classified as unsuitable, with anticipated low CBCT quality.

Visually, both images appear similar, underscoring the challenge of manually determining CBCT adequacy. This demonstrates the clinical value of the deep learning model, which identifies subtle, non-obvious features in the simulation CT that correlate with CBCT quality. The model's predictions were consistent with clinical assessments, supporting its potential for integration into the ART decision-making process.

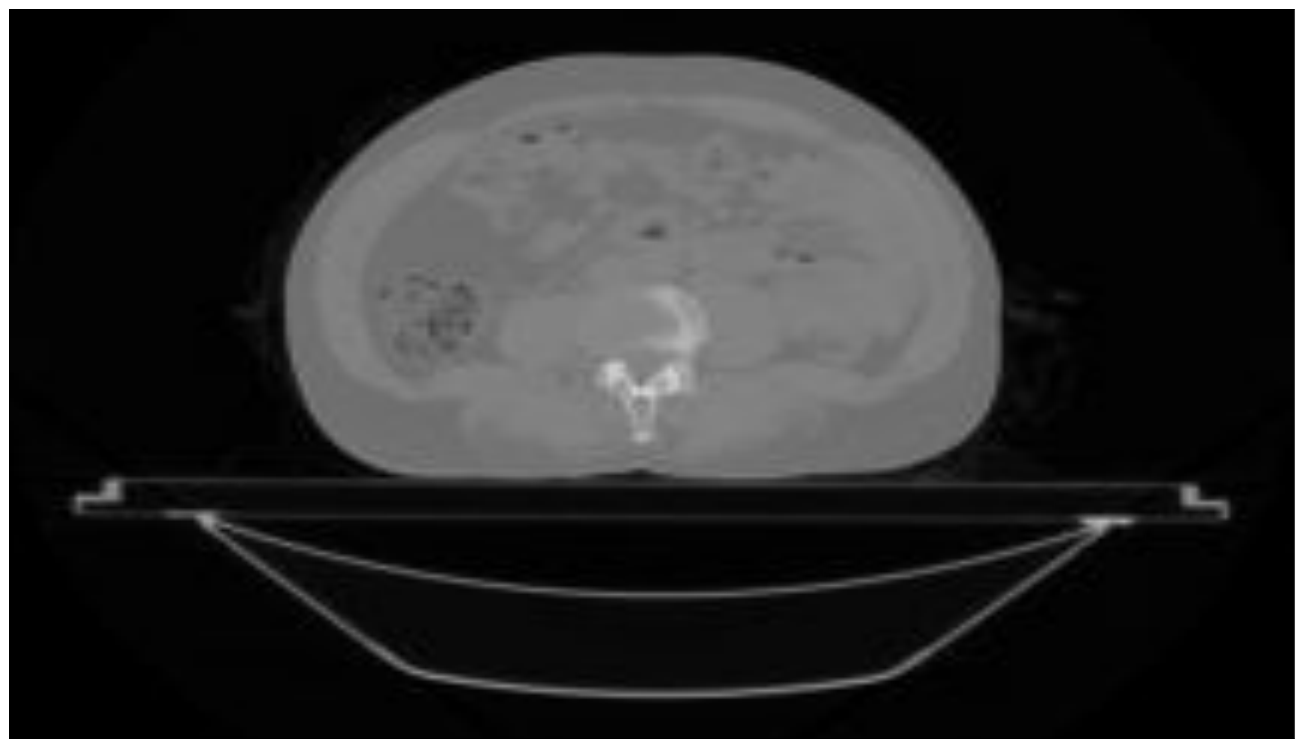

Figure 1: Sim CT of a patient classified as suitable for ART, with anticipated high CBCT quality.

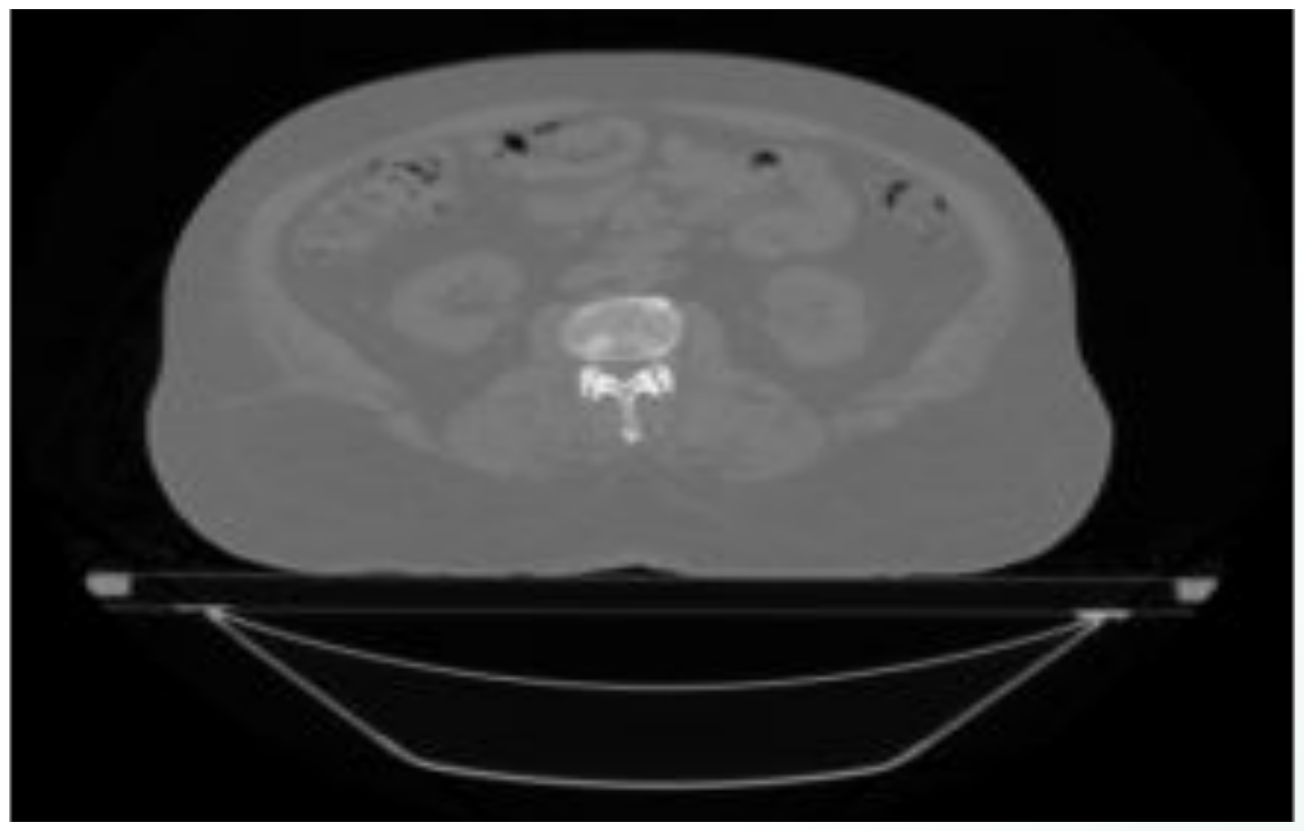

Figure 2: Sim CT of a patient classified as unsuitable for ART, with anticipated low CBCT quality.

Discussion/Conclusion

This proof-of-concept study demonstrated the potential of deep learning for predicting patient suitability for Ethos based adaptive radiotherapy. While it showed promising results, the current model trained on a small and imbalance cohort of 30 patients, including only 5 non-adaptive and 25 adaptive cases, which may limit the generalizability of the findings. Larger and more balanced datasets are needed to validate and strengthen these preliminary results.

This study introduces a decision-support tool that could potential help clinicians determine whether a patient is likely to benefit from adaptive radiotherapy. By implementing this approach, clinics can reduce unnecessary treatment replanning, minimize treatment delays, and optimize clinical workflow (ART/IGRT). Future work will focus on expanding the dataset, refining the classification algorithm, and prospectively validating its performance in clinical practice.

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