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# AI-Denoising Methods for Real-time Multi-particle Monte Carlo Dose Calculations Covering Photons, Protons, and Neutrons

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## ABSTRACT

**Purpose:**
External-beam therapy now includes various particles such as photons, protons, carbon ions and recently neutrons in Boron Neutron Capture Therapy (BNCT). Accurate and speedy dose calculational algorithms are intergral to the clinical workflow of treatment planning and QA verification. With the advent of powerful deep-learning (DL) tools, it is possible to perform Monte Carlo (MC) dose simulations in real-time, taking a fraction of a second. This study proposes a unified real-time MC dose engine covering multiple radiation modalities using a lightweight DL-based denoising framework.
**Methods:**
The framework integrates the ARCHER GPU-based MC dose engine with a hybrid DL denoising model. A unified lightweight architecture based on Enhanced Difference Ghost Shuffling reduces model parameters by up to 90% compared to conventional 3D-UNets while preserving high-frequency dose gradients. A strict energy-conservation constraint is incorporated to enhance physical consistency and interpretability. This model was trained and validated on a large multi-particle dataset containing over 600 3D plans for patients, including photons (190 cases), protons (175 cases), and BNCT (90 cases). The Gamma Passing Rate (GPR) and Mean Absolute Percentage Error (MAPE) were used for quantitative evaluation.
**Results:**
For photons, protons, and carbon ions, GPR (2%/2 mm) exceeded 95.2%. In BNCT cases, MAPE ranged from 2%–5% for organs at risk, with GTV dose deviations (D98, D95) below 3.5%. The method preserved sharp tumor dose gradients. Using an NVIDIA RTX 3090 GPU, the full pipeline (GPU-based simulations + AI denoising) achieved ~0.8 s for photons, protons, and <27 s for BNCT neutrons.
**Conclusions:**
By integrating a lightweight and physically constrained DL-based hybrid denoising algorithm, we have demonstrated the feasibility of extremely fast MC calculations for various types of radiation therapy particles, including neutrons in complex BNCT.

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## INTRODUCTION

Accurate and rapid dose calculation is essential for treatment planning, adaptive radiotherapy, and quality assurance. Monte Carlo methods provide the highest physical accuracy, but low-particle simulations contain significant stochastic noise, and high-particle simulations are computationally expensive.
Recent deep-learning methods have accelerated MC dose denoising, yet many existing approaches are modality-specific or rely on relatively heavy architectures.
In this work, we present a unified AI-denoising framework for real-time multi-particle MC dose calculations covering photons, protons, and neutrons in BNCT.

## METHODS AND MATERIALS

**Framework overview:**.
• A unified EDGS-based denoising network learns the mapping from low-particle maps to high-particle reference maps.
• A physics-based energy-conservation constraint is incorporated to improve dose consistency and interpretability.

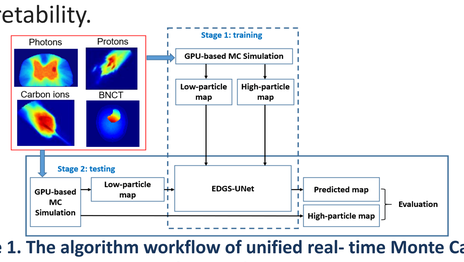


Figure 1. The algorithm workflow of unified real- time Monte Carlo dose engine.

$$loss_1 = \frac{1}{|body|} \times \sum_{j \in body} log\left(\left(exp\left(D^j_{denoised} - D^j_{GT}\right) + exp\left(-D^j_{denoised} + D^j_{GT}\right)\right)/2\right)$$

Figure 2. Physics-based energy-conservation constraint .

**Network design:**
• The network is built upon Enhanced Difference Ghost Shuffling modules to reduce computational burden while maintaining high-frequency dose-gradient information.
• Residual shuffling and hierarchical channel–spatial–pixel attention improve feature extraction and multi-scale dose restoration.
• Compared with conventional 3D-UNet models, the number of trainable parameters is reduced by approximately 90%.

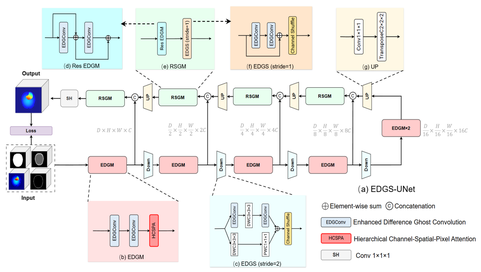


Figure 3. The architecture of the Enhanced Difference Ghost Shuffling network.

**Dataset and evaluation:**
• Multi-particle dataset: photons (190), protons (175), and BNCT (90), totaling > 400 3D plans.
• Evaluation metrics: include Gamma Passing Rate (2%/2 mm),Mean Absolute Percentage Error (MAPE)

## RESULTS

As shown in Fig 4, the unified engine demonstrated consistently high accuracy and efficiency across all supported particle types. For photon, and proton radiotherapy, the Gamma Passing Rate (2%/2 mm) exceeded 95.2%, the complete GPU simulation + AI denoising pipeline requiring less than 0.8 seconds per case, and AI inference time approximately 0.1 seconds, using the NVIDIA GeForce RTX 3090 GPU card. For recently emerging BNCT—the most computationally demanding modality—the method achieved MAPE values of 2%–5% for organs at risk and maintained GTV D98/D95 deviations within 3.5%. The total computation time was reduced to under 27 seconds. Figure 5 presents the comparison chart of DVH after denoising for different particles.

Table 1. Summary of performance and efficiency for different particle types.

| Particle | Cases | Main metric | Performance | Time |
|---|---|---|---|---|
| Photon | 190 | GPR (2%/2 mm) | >95.2% | ~0.8 s |
| Proton | 175 | GPR (2%/2 mm) | >98.9% | ~0.5 s |
| BNCT | 90 | GPR (2%/2 mm) | >97.0% | <27 s |

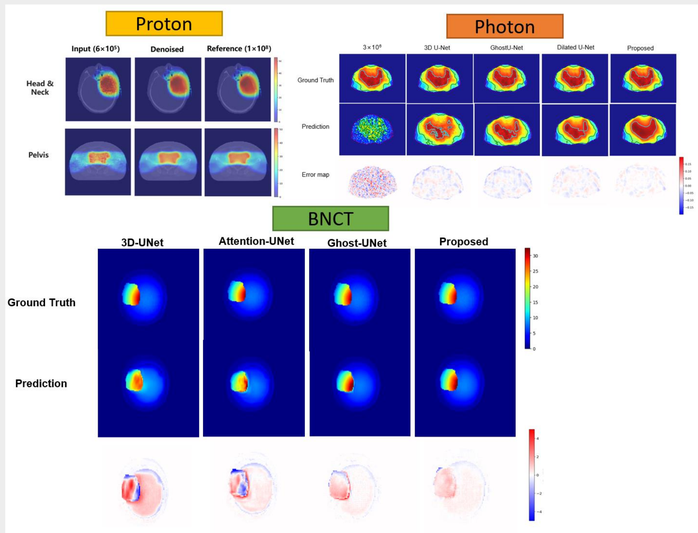


Figure 4. Comparison of photons, protons and BNCT with the dose and dose-difference distribution maps of SOTA models.

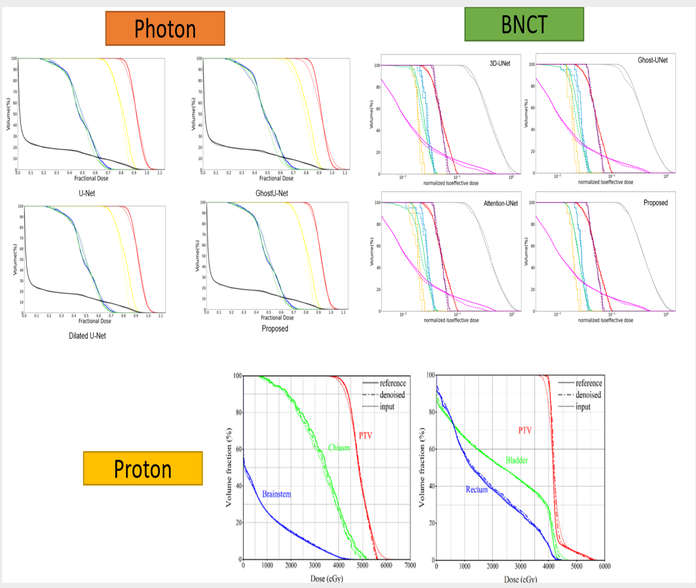


Figure 5. Comparison of DVH of photons, protons and BNCT with SOTA models.

## DISCUSSION

• The proposed study demonstrates that a single lightweight denoising framework can support multiple radiation modalities without sacrificing performance. This is particularly important because particle-specific solutions can be difficult to maintain and scale in clinical environments.

• The EDGS-based design preserves sharp dose gradients while drastically reducing model complexity, making real-time deployment more practical.

• The framework is especially promising for treatment planning and quality assurance workflows that require rapid and repeated MC calculations.

• BNCT remains the most challenging modality due to its complex neutron transport characteristics, yet the current results still show clinically encouraging dose agreement and substantial acceleration.

• Overall, the method provides a unified and scalable computing platform for modern radiotherapy dose calculation.

## CONCLUSIONS

• A unified real-time Monte Carlo dose engine was developed for photons, protons, carbon ions, and neutrons in BNCT.

• The lightweight EDGS-based denoising framework reduced model parameters by about 90% compared with conventional 3D-UNet designs.

• Excellent quantitative agreement was achieved across modalities, including GPR >95.0% for photons, protons, and BNCT OAR MAPE of 2%–5% with GTV D98/D95 deviations <3.5%.

• The proposed framework demonstrates strong potential for real-time treatment planning, adaptive radiotherapy, and radiotherapy QA.

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