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Resnet Deep Learning Convolutional Neural Networks for Halcyon Based Portal Dosimetry 2D Dose Plane Gamma Passing Rate Predictions

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Purpose: Developing and researching methods of implementing deep learning neural networks capable of predicting gamma passing rates (GPRs) from retrospective 2D dose plane images for QA procedure optimization, workflow improvements, and plan delivery.

Methods: A dataset built from 184 DICOM files collected from 87 patients that underwent IMRT and FSRT prostate cancer procedures on a Halcyon Linear Accelerator was created in conjunction with the use of ResNet architecture to act as a feature extractor. Dose normalized data was loaded and preprocessed into an appropriate format to match the expected inputs for the used ResNet model, and an 80/20 training validation split was used. ResNet layers/ weights were frozen to prevent overfitting from a small sample size by limiting changeable parameters, while loss and optimizers were chosen to prevent large errors and optimal regression. The training loop then looked at small batches of data and optimized for regression loss per epoch and for evaluation, validation, and backpropagation. Fine-tuning is then done by unfreezing layers and experimenting with parameters and learning rates. The results are then measured in mean absolute error and root mean squared error and graphed to show predicted gamma passing rates vs the actual gamma passing rates.

Results: Error metrics of around 4 percent mean absolute error and 5 percent root mean squared error were found after training and validation, while avoiding overfitting and keeping complexity. Our coefficient of determination, R-squared, varied around zero with noise.

Conclusion: There is potential in the use of Deep Learning for predicting 2D dose plane GPR, although further testing and improvements are needed. Experimenting with weights, hyperparameters, learning rate, larger datasets, and testing higher-layer models of ResNet, such as ResNet50 or ResNet34 are likely to increase the performance of the model and reach a higher correlation.

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INTRODUCTION

ResNet is a deep learning architecture that uses **residual connections** to overcome the vanishing gradient problem, enabling the training of deeper neural networks such as **ResNet-18, ResNet-50, and ResNet-152**. This project investigates the use of **ResNet-18** to predict **Gamma Passing Rates (GPRs)** from retrospective **2D dose plane images**, with the goal of improving patient-specific quality assurance (QA), optimizing clinical workflow, and supporting accurate radiotherapy treatment delivery.

METHODS

A dataset consisting of **184 DICOM dose plane images** from **87 prostate cancer patients** treated with **IMRT** and **FSRT** on a **Varian Halcyon Linear Accelerator** was used to develop a deep learning model for predicting Gamma Passing Rates (GPRs). Dose values were normalized, and DICOM pixel data were extracted using **PyDICOM**. A custom **PyTorch Dataset** was created to pair each image with its corresponding GPR from a CSV file. Images were converted into a three-channel (RGB) format to match the input requirements of **ResNet-18** (Figure 1), and the dataset was divided into **80% training** and **20% validation** sets.

ResNet-18 was selected as the backbone architecture due to the limited dataset size, reducing the risk of overfitting while leveraging **transfer learning** from pretrained ImageNet weights. During initial training, pretrained layers were frozen to preserve learned image features and limit the number of trainable parameters. Fine-tuning was subsequently performed by gradually unfreezing layers and optimizing learning rates. The model was trained using mini-batch gradient descent with backpropagation, and multiple regression loss functions, including **Mean Squared Error (MSE)** and **Huber Loss**, were evaluated. Model performance was assessed using **Mean Absolute Error (MAE)** and **Root Mean Squared Error (RMSE)**, with predicted GPRs compared against measured GPRs through regression analysis. The ResNet architecture utilizes convolutional layers to extract hierarchical image features and pooling layers to reduce feature dimensionality, enabling efficient learning from 2D dose distributions.

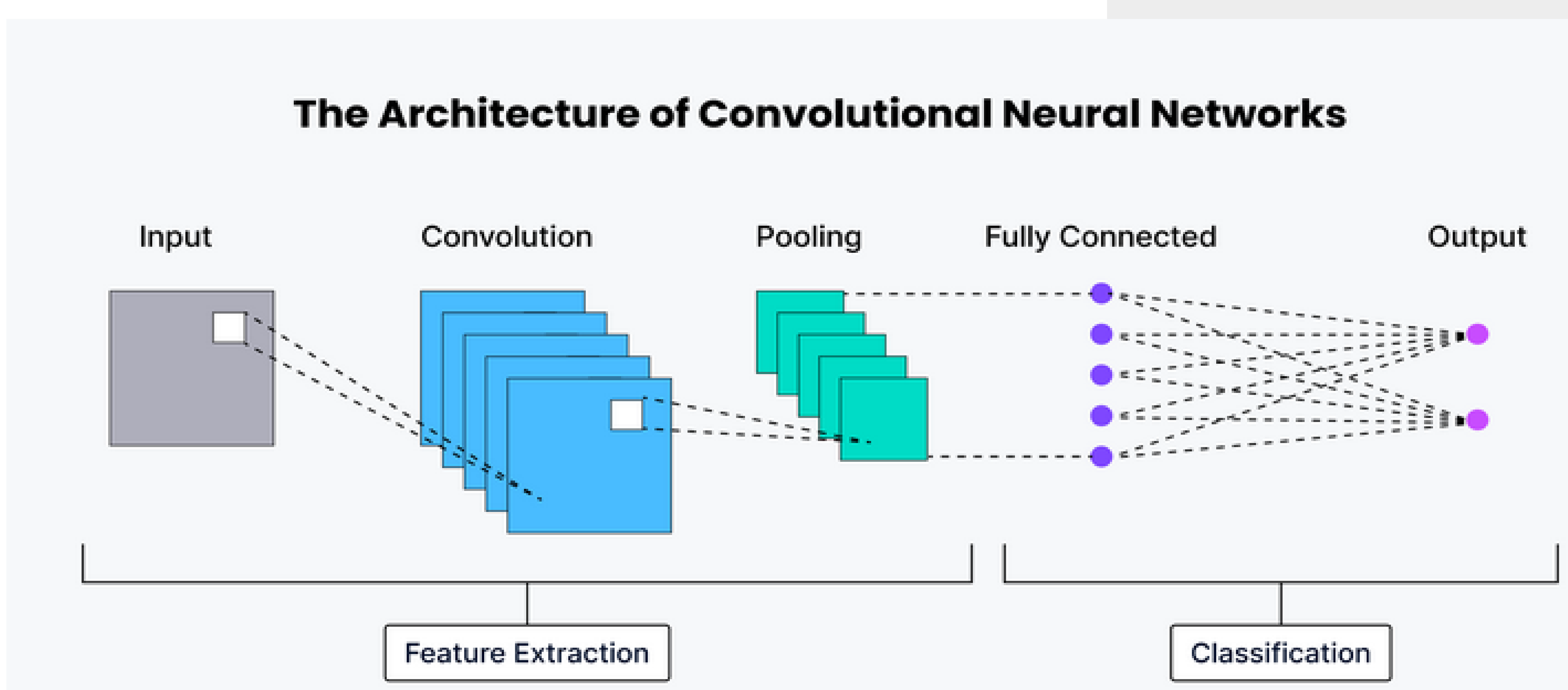

Figure 1. ResNet-18 architecture used in this study. Because ResNet expects RGB input images, the input dose profiles were re-formatted into a three-channel representation compatible with the network.

RESULTS

The trained ResNet-18 model achieved a **Mean Absolute Error (MAE)** of approximately **4%** and a **Root Mean Squared Error (RMSE)** of approximately **5%**, representing an improvement over the initial model performance (approximately **7% MAE** and **6% RMSE**). The use of transfer learning and fine-tuning helped improve predictive accuracy while minimizing overfitting despite the limited dataset.

However, the model produced an **R^2 value close to zero**, indicating that it did not adequately capture the relationship between the predicted and measured GPRs. This suggests that the extracted image features were insufficient for reliable prediction.

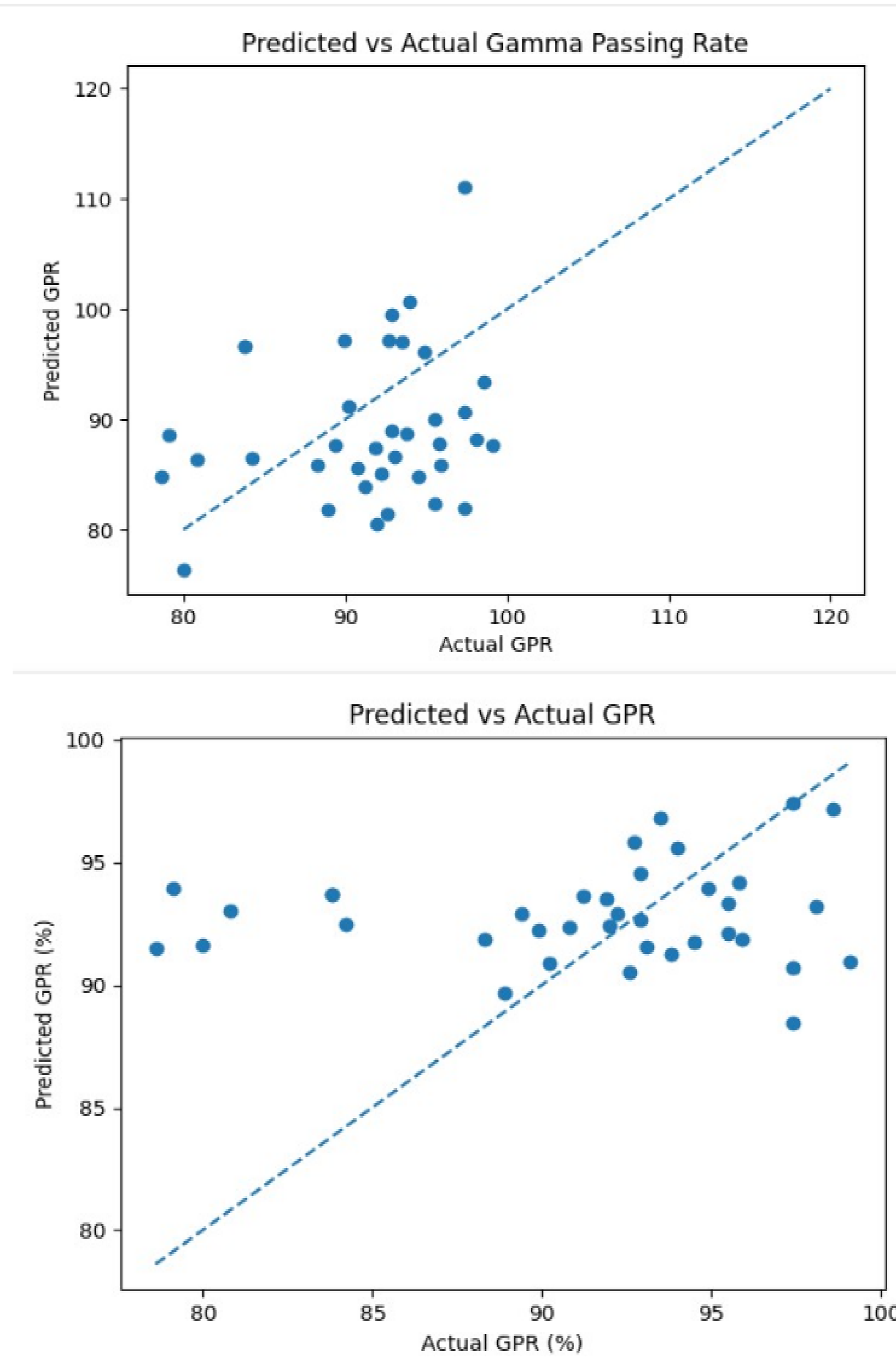

Figure 2. Predicted vs actual gamma passing rate.

DISCUSSION

The limited dataset presents a significant challenge for developing accurate deep learning models, highlighting the need for expanded training data and improved methodologies. Because acquiring large clinical datasets is often difficult, this work will investigate **Physics-Informed Neural Networks (PINNs)** as an alternative approach. PINNs incorporate known physical principles into the learning process, allowing models to leverage both clinical data and the underlying physics governing radiotherapy delivery.

Future work will integrate additional treatment machine information, including **linear accelerator (LINAC) parameters**, **multileaf collimator (MLC) positions**, machine output, and delivery timing. These features may provide stronger correlations with Gamma Passing Rates (GPRs) than dose images alone. By combining image-based learning with physics-informed constraints and machine delivery data, the proposed approach aims to improve prediction accuracy while reducing the amount of training data required, offering a computationally efficient alternative to traditional Monte Carlo–based methods for patient-specific quality assurance.

CONCLUSIONS

This study demonstrates the potential of **deep learning** for predicting **2D dose plane Gamma Passing Rates (GPRs)**, although further optimization is required to improve predictive performance. Future work will investigate deeper ResNet architectures (e.g., **ResNet-50** and **ResNet-101**), larger datasets, and optimization of hyperparameters, learning rates, and feature weighting to improve model accuracy and correlation. Additionally, **Physics-Informed Neural Networks (PINNs)** will be explored to incorporate radiotherapy physics and treatment machine data, reducing overfitting and improving feature extraction. These advances have the potential to enhance predictive quality assurance and support more efficient, reliable clinical radiotherapy workflows.

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