Deep Feature-Driven SVM Modeling for Arc-Level Quality Assurance In Prostate Radiotherapy

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2026 JULY 19–22 VANCOUVER, BC
JOINT AAPM | COMP MEETING

Purpose: The aim of this work is to predict the arc level gamma passing rate (GPR) values for IMRT, and FSRT plans at the prostate site using machine learning-based models using the SVM algorithm.

Methods: Here Support Vector Machine (SVM), a supervised max-margin model is used for regression analysis between dose and GPR. A total of 82 prostate treatment plans, comprising 198 arcs, were analyzed. Dose planes originally sized at 1280×1280 for IMRT and FSRT normalized to ensure consistent spatial representation. A pretrained ResNet model with frozen weights was used to extract deep features. ResNet34 captures the dose gradient characteristics and spatial modulation patterns. The original high dimensional feature set was reduced to 37 informative predictors using a multistage feature selection pipeline that included variance thresholding, correlation filtering, mutual information scoring, and recursive feature elimination. A linear and RBF kernel SVM model with 10-fold cross validation was trained using these features. Root mean square error(RMSE), mean absolute error(MAE) , coefficient of determination, and Pearson correlation coefficient were used to assess the model's performance.

Results: . Strong agreement between predicted and measured gamma passing rates was demonstrated by the model's RMSE of 2.64 percent, MAE of 2.18 percent, R2 of 0.58, and correlation of 0.79. 58.3% and 54.2% of predictions, respectively, fell within the corresponding tolerance bands under the 2% and 3% gamma criteria.

Conclusion: These results show that the suggested model offers clinically significant accuracy and consistently captures arc level variations. The machine learning model provides a way to lessen the workload associated with patient-specific quality assurance, and further research will expand this approach to other anatomical sites to facilitate the creation of a universal prediction model.

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INTRODUCTION

Patient-specific quality assurance (PSQA) is essential for verifying the accuracy of dose delivery in intensity-modulated radiation therapy (IMRT) and volumetric modulated arc therapy (VMAT). However, conventional measurement-based PSQA is labor-intensive and time-consuming. Machine learning (ML) and deep learning (DL) methods have been developed to predict gamma passing rates (GPRs) using treatment plan and dosimetric features [1].

Pretrained convolutional neural networks (CNNs), such as ResNet-34, can automatically extract high-level image features from DICOM dose distributions, eliminating the need for manual feature engineering [2–4]. These deep features can then be used as inputs to support vector machine (SVM) models for GPR prediction and PSQA pass/fail classification.

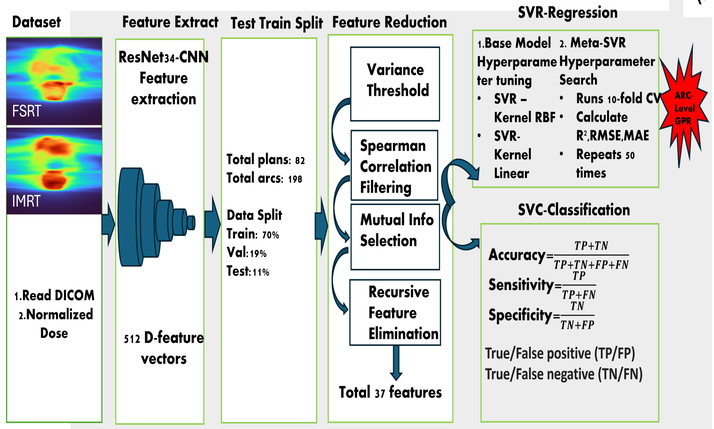

Figure 1. Architecture of the pretrained ResNet-34 feature extraction network and the support vector machine (SVM) models used for gamma passing rate prediction and PSQA pass/fail classification.

DATASET AND METHODOLOGY

Figure 1 shows the architecture of the pretrained ResNet-34 and the SVM models used for this study. The dataset consisted of 82 IMRT/FSRT treatment plans, comprising 198 treatment fields. The predicted two-dimensional (2D) dose distributions were normalized and used as inputs to the pretrained ResNet-34 with frozen weights, which extracted a 512-dimensional feature vector for each dose plane. GPRs were calculated from phantom-based PSQA measurements using a 2%/1 mm gamma criterion, a 10% low-dose threshold, and a 95% passing criterion.

The dataset was randomly divided into training (70%), validation (19%), and testing (11%) sets. Feature selection was performed using variance thresholding, correlation filtering, mutual information ranking, and recursive feature elimination. The selected features were used to train Support Vector Classification (SVC) models with linear and radial basis function (RBF) kernels for pass/fail classification and Support Vector Regression (SVR) models for continuous GPR prediction. Model performance was evaluated using the independent test set.

RESULTS

At the 2%/1mm gamma criterion in test set, the stacking SVR model combining linear and RBF kernels achieved RMSE = 2.64, MAE = 2.18, R^2 = 0.577, and Pearson CC = 0.792 shown in figure 2. The linear SVR captured global dose–GPR trends, while the RBF SVR modeled nonlinear modulation complexity. The meta-SVR effectively fused both representations, improving predictive accuracy and demonstrating that complementary kernel behaviors enhance generalization. Tolerance analysis in figure 2 showed 58.3% of predictions within ±3% and 54.2% within ±2%. Classification performance was evaluated on the independent test set to ensure unbiased assessment. Linear SVM achieved the highest accuracy but showed overfitting (AUC = 0.317).

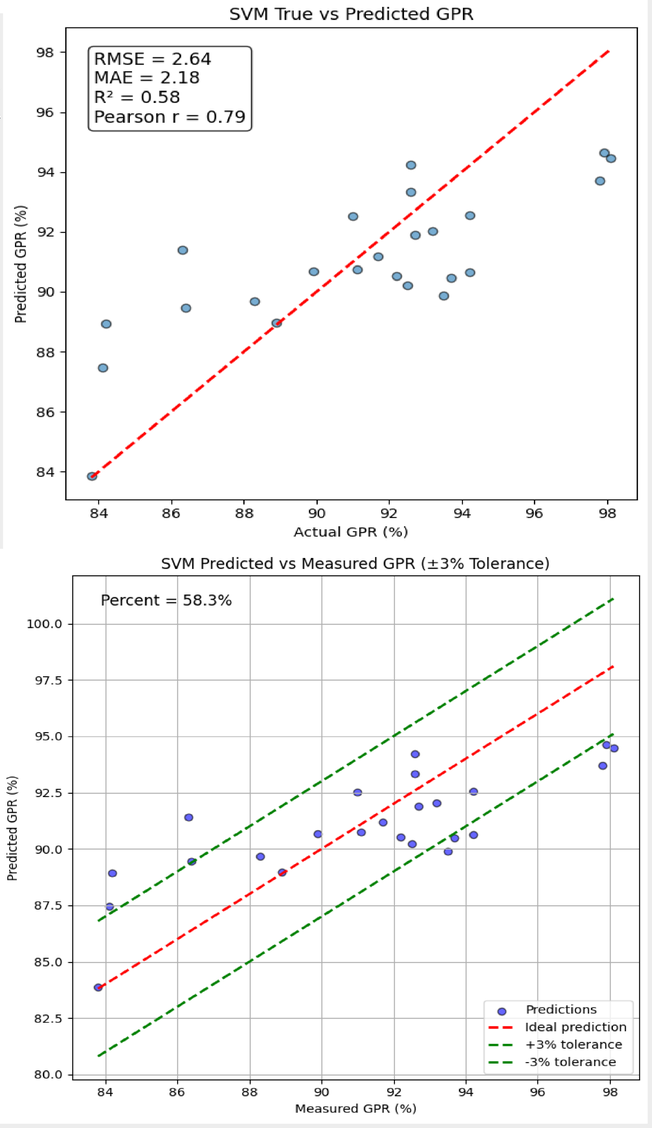

Figure 2. (upper) Scatterplots of measured versus predicted GPRs in the test dataset and (lower) ±3% tolerance plot.

DISCUSSION

Gamma passing rate is not arbitrary. The staking SVR able to get correlation of 0.79 between predicted and measured GPR implies that the model captures the true physical relation between dose patterns and gamma outcomes. Hybrid models (Linear + RBF) provide the best performance. Gamma is influenced by spatial features like gradients, modulation and fluence complexity. Deep CNN features able to capture these features[2,3,4].

Best AUC(0.746) is for linear SVM indicated that the global linear trends dominate the gamma behavior. Although RBF SVM has high accuracy (0.875), but the value of AUC is low (0.317) indicating nonlinear patterns do exist, but RBF kernel overfits due to data limitation.

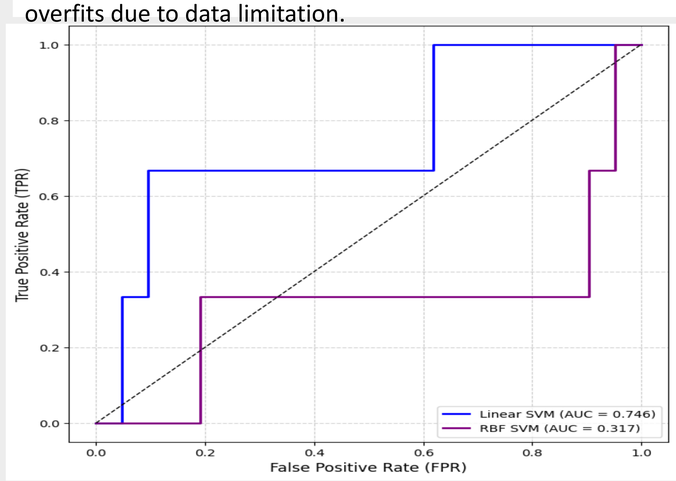

Figure 3. ROC curves of the three classification models for the 2 %/1mm criteria in the test dataset.

Table 1. Classification matrix comparison between linear and RBF kernel

	Linear	RBF
Accuracy	0.708	0.875
Sensitivity	0.667	0.667
Specificity	0.714	0.905
AUC	0.746	0.317

CONCLUSIONS

The proposed ResNet-34 and Support Vector Machine (SVM) model successfully predicted gamma passing rates (GPRs) for IMRT/FSRT treatment plans. The strong performance suggests that GPR information is encoded in the spatial characteristics of the dose distribution. Future work will investigate treatment plan complexity metrics that correlate with the extracted deep features and GPR prediction.

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