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Predicting heart dose in left-sided breast cancer patients using volumetric modulated arc therapy: an anatomical feature-driven machine learning model

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Original Article

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Abstract

The purpose of this study was to establish a machine-learning model that predicts heart dose in left-sided breast cancer patients treated with volumetric modulated arc therapy (VMAT). As radiotherapy (RT) poses an increased risk of cardiac toxicity, the model employs anatomical features to predict heart dose, tackling a significant issue in the management of breast cancer. This retrospective analysis focused on 53 patients with left-sided breast cancer who received VMAT RT. Various partial arc VMAT techniques were assessed, including the 2P, 4P and 5P methods. Key anatomical parameters measured included mean heart distance (MHD), total heart volume (THV) within the treatment field, heart volume (HV) and planning target volume (PTV). Elastic Net regression models were created to forecast heart dose metrics associated with different VMAT techniques. The Elastic Net regression models successfully predicted heart dose metrics, with VMAT-4P achieving the best performance, reflected in the lowest root mean squared error (RMSE) of 0·9099 and a median absolute error (MEDAE) of 0·5760 for the mean dose. VMAT-5P was particularly effective in predicting V5Gy, with an RMSE of 4·8242 and a MEDAE of 2·1188, while VMAT-2P recorded the lowest MEDAE for V25Gy at 1·0053. The feature importance analysis highlighted MHD as the primary predictor, contributing 75%, followed by THV at 18%, HV at 4% and PTV at 3%. The findings of this study emphasise the critical need to consider patient-specific anatomical features and the effectiveness of VMAT techniques in the treatment planning for left-sided breast cancer. The predictive models established present a pathway for personalised treatment enhancement. Treatment planners are encouraged to assess a range of anatomical characteristics when choosing the optimal VMAT technique.

Introduction

Breast cancer continues to pose a major global health issue, with 2·3 million new diagnoses and 685,000 fatalities recorded worldwide in 2020. As the most frequently diagnosed cancer in women, projections indicate that cases could surpass 3 million by 2040.[1] The increasing burden, especially in transitioning nations where both incidence and mortality rates are elevated, highlights the urgent requirement for enhanced treatment options and focused interventions.[2] Approximately 50% of these cases affect the left breast, which poses unique challenges for radiation therapy due to the close proximity of the heart.[3] Although adjuvant radiotherapy (RT) enhances locoregional control and increases survival rates, the long-term implications of radiation toxicity, especially the heightened risk of cardiac issues such as coronary artery disease, are critical considerations for patients diagnosed with left-sided breast cancer.

The pivotal research conducted by Darby et al. demonstrated a direct relationship between the average heart dose and the occurrence of significant coronary events, indicating a concerning 7·4% rise in risk for each grey of exposure.[4] Numerous aspects contribute to cardiotoxicity, surpassing the average heart dose considerations. Addressing these challenges, the field of radiation oncology has seen substantial advancements in technology. Despite the effectiveness of Deep Inspiration Breath Hold in lowering cardiac exposure, it is not a viable option for every patient.[5] Therefore, it is essential to utilise free-breathing techniques that yield comparable heart-protective outcomes.

Volumetric modulated arc therapy (VMAT) has become a noteworthy technique, demonstrating the ability to achieve enhanced dose conformity and greater sparing of organs-at-risk (OARs) relative to conventional treatment approaches.[6] The capability of VMAT to deliver radiation through continuous gantry rotation combined with dynamic multileaf

collimator modulation provides significant flexibility in dose optimisation, potentially allowing for enhanced heart avoidance while ensuring comprehensive target coverage.[7] Research into the optimisation of VMAT for left-sided breast cancer treatment is ongoing. A variety of arc configurations, including both partial and full arcs, have been explored, each associated with distinct dosimetric effects.[8,9] However, in spite of these advancements, the ability to accurately predict heart dose is still critical in treatment planning, as it direct influence on the efficacy of VMAT in minimising cardiac risk.

The precise prediction of heart dose plays a vital role in the planning of treatment, as variables such as patient anatomy, breathing patterns and daily setup can alter the actual dose received.[10] Thus, accurate heart dose prediction is essential for managing left-sided breast cancer effectively, highlighting the need for the development of strong models to refine treatment plans and mitigate cardiac risk. Various anatomical factors have been studied as possible predictors of heart dose in conventional RT, such as maximum heart distance (MHD) and central lung distance.[11,12]

In the past decade, the integration of artificial intelligence and machine learning (ML) techniques has become more prevalent in the area of RT.[13–16] Despite this trend, there are few studies that have focused on using ML to predict the MHD during RT based on patient data.[17–20] The relevance of anatomical predictors in the context of VMAT planning is not clearly defined, and their relationship with different VMAT arc configurations has not been extensively investigated.

However, Elastic Net regression, developed by Zou and Hastie in 2005,[21] effectively integrates the benefits of Ridge and Lasso regression, making it particularly effective in situations where the significance of predictor variables is unclear. This technique not only enhances model fitting efficiency but also performs feature selection, as indicated by Friedman et al. in 2010.[22] Ridge regression is adept at addressing multicollinearity among predictor variables, while Lasso regression is focused on identifying the most influential factors affecting outcomes. By capitalising on the strengths of both Ridge and Lasso, Elastic Net provides a formidable tool for uncovering critical predictors in complex datasets.

Therefore, the purpose of this study is to evaluate the performance of Elastic Net models in predicting heart dose metrics across multiple VMAT techniques in patients with left-sided breast cancer undergoing RT. Additionally, we will apply Elastic Net models for feature selection to identify significant anatomical predictors of heart dose.

Methods and Materials

Study design and patient selection

A retrospective analysis was performed involving 53 female patients diagnosed with left-sided breast cancer who underwent VMAT RT at the State Cancer Institute, Indira Gandhi Institute of Medical Science, Patna, Bihar, within the Department of Radiation Oncology and Medical Physics, from December 2022 to June 2024. Eligible participants included women aged 18 and older with histologically confirmed left-sided breast cancer, who received VMAT treatment and had comprehensive medical records detailing Tumor, Node, Metastasis (TNM) staging and receptor status. Exclusion criteria encompassed male breast cancer patients, those with right-sided breast cancer, individuals diagnosed with metastatic disease, incomplete medical records, patients who did not receive VMAT RT, those who had not completed their treatment and pregnant women. The study received approval from the institutional review board.

Patient characteristics

The characteristics of the 53-patient population demonstrated notable diversity, emphasising the complex presentations associated with breast cancer. The median age among participants was 47 years, with a range from 29 to 76 years. Tumour stages were classified from T1 to T4, and nodal involvement was recorded from N0 to N3 after modified radical mastectomy. The study included patients treated both before and after neoadjuvant therapy. Additionally, there was notable variability in hormone receptor (ER/PR) and HER2 status among the patients, with a mix of both positive and negative cases for each.

CT simulation and contouring

The CT simulation was executed with a GE Revolution EVO CT simulator, which had a slice thickness of 2·5 mm. Patients were positioned supinely and immobilised using a two-clamp thermoplastic mask on an integrated breast board, which was set to an appropriate wedge angle. The affected arm was abducted and held at an angle of 90 degrees or more, while the head was turned towards the opposite side. Reference points were established by placing fiducials on the chest wall, both centrally and laterally on each side. The CT images were imported into the Eclipse planning system using DICOM. The delineation of the Clinical Target Volume, planning target volume (PTV) and OARs, including the heart and lungs, was carried out following the guidelines set forth by the Radiation Therapy Oncology Group protocol.

Treatment planning

The Eclipse treatment planning system (TPS) (version 16·1, Varian Medical Systems, USA) was used to develop and enhance treatment plans, which were then executed with a Varian TrueBeam SVC linear accelerator equipped with Millennium 120 multileaf collimators. Three separate VMAT planning methods utilising partial arcs with 6MV photon beam were applied. The two-partial arc method (V-2P) consists of a clockwise arc spanning from 295–300° to 160–165°, with the collimator angle adjusted to +30°. This is followed by a counterclockwise arc that returns from 160–165° back to 295–300°, utilising a collimator angle of −30°. The four-partial arc method (V-4P) builds upon the V-2P technique by adding two more arcs: a clockwise arc from 300° to 41° with a collimator angle of 35°, and a counterclockwise arc from 165° to 80° with a collimator angle of 345°. This method employs jaw splitting to minimise exposure to the lungs and heart. The beam-eye view is shown in Fig. 1(a). The five-partial arc method (V-5P) further refines the planning approach by integrating all five arcs with jaw splitting: Arc 1 from 310° to 41° at a collimator angle of 17°, Arc 2 from 81° to 160° at 343°, Arc 3 from 331° to 160° at 80°, Arc 4 from 160° to 81° at 357° and Arc 5 from 41° to 310° at 3°and the beam-eye-view is shown in Fig. 1(b).

The VMAT plan was optimised using the Photon Optimizer, and the final calculations were carried out with the Anisotropic Analytical Algorithm, employing a grid size of 2·5 mm throughout the process. The treatment plan prescribed a total dose of 40·05 Gy, administered in 15 fractions over a 3-week duration. The optimisation goals included:

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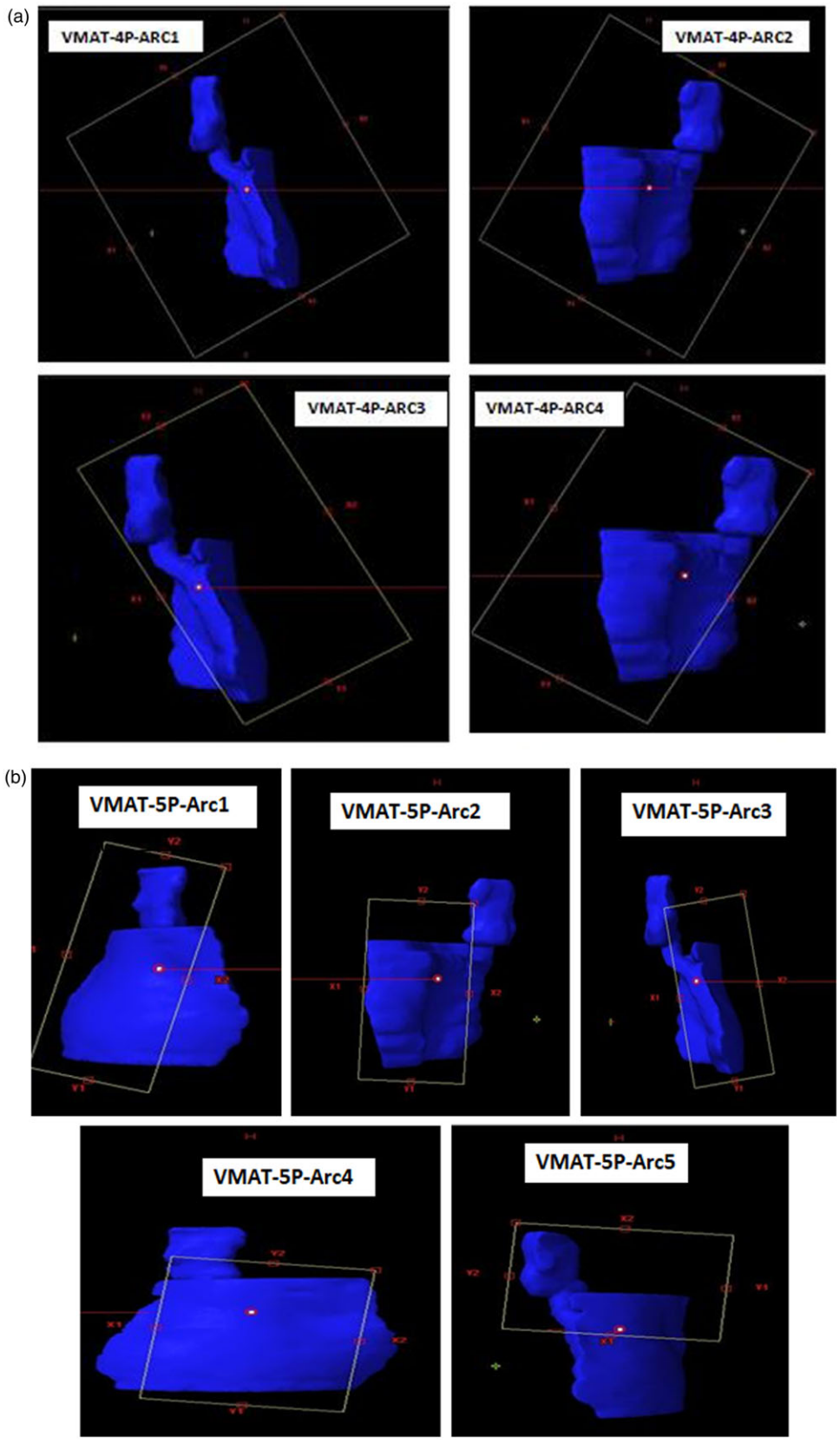

Figure 1. (a) Beam-eye view of beginning setup in four-partial arc VMAT techniques. (b) Beam-eye view of beginning setup in five-partial arc VMAT techniques.

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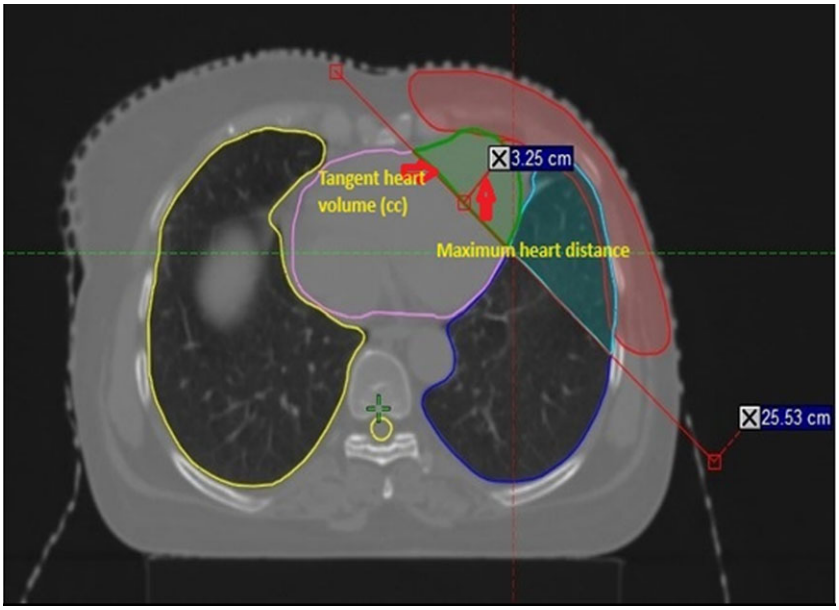

Figure 2. Shows the maximum heart distance and tangent heart volume in field measurements.

- Ensuring that 95% of the PTV receives the prescribed dose (not exceeding 107%).
- Limiting the mean heart dose to ≤ 5 Gy, with V5 ≤ 20% and V25 ≤ 10%.
- Restricting the mean lung dose to ≤ 15 Gy, with V5 ≤ 65%, V10 ≤ 40%, and V20 ≤ 30%.
- Contralateral lung and breast mean dose less than 3Gy.

Anatomical parameters measurements

In order to find the centre of the target on the central axial CT slice, one must first identify the midpoint of the PTV along the cranial-caudal axis. This can be accomplished either through direct visual inspection of the CT slices or by utilising a measurement tool within the TPS to determine the cranial-caudal distance of the PTV and dividing that figure by two. Subsequently, tangent lines should be drawn from both the lateral and medial edges of the tangential posterior margin of the PTV. The maximum distance from the tangent line to the anterior surface of the heart is measured in centimetres, which is referred to as the MHD. The volume of the heart that lies above the tangent line is calculated using the TPS and reported in cubic centimetres (cc), known as the total heart volume (THV) in the field.[23] Additionally, the volume of the contoured heart is termed the Heart Volume (HV) and the volume of the contoured PTV is computed and expressed in cubic centimetres (cc), recognised as the PTV as demonstrated in Fig. 2.

Modelling approach

For this study, the dataset was assembled with the aim of training and evaluating the Elastic Net model as demonstrated in Fig. 3(a) & 3(b). The significance of the predictor variables was assessed by extracting feature importance from the Elastic Net model as demonstrated in Fig. 3(c).

Statistical analysis

Elastic net model performance and feature importance

This process required reading the Comma-Separated values (CSV) file containing patient records and discarding the third column from the data frame. The predictor (X) and target (y) variable values were then extracted from the data frame. Finally, the dataset was divided into training (70%) and testing (30%) sets to allow for effective model evaluation and its effectiveness was evaluated on the separate test set. The assessment utilised root mean squared error (RMSE) and median absolute error(MEDAE) as the metrics for evaluation.

The significance of the predictor variables was assessed by extracting feature importance from the Elastic Net model as demonstrated in Fig. 3(c). Initially, the target variable (Heart mean doses) was removed from the list of feature names. The feature importance values were subsequently normalised to total of 1, allowing for an accurate evaluation of each variable's relative contribution. Finally, these values were arranged in descending order to highlight the most impactful predictors.

Results

This investigation demonstrated that all VMAT plans met the clinical benchmarks for PTV coverage, ensuring that at least 95% of the prescribed dose was delivered without any hotspots exceeding 107%. The sparing of OAR was consistently achieved, with the Mean Heart Dose (MHD) maintained at ≤ 5 Gy and lung and heart dose-volume parameters adhered to specified limits. Moreover, the average dose to the contralateral lung and breast was kept below 3 Gy. Importantly, our findings stressed the role of anatomical features in predicting heart dose.

Anatomical features

Tables 1 and 2 demonstrated the heart parameters associated with the various VMAT techniques utilised in this study. The assessment included the heart mean dose, heart V5Gy and heart V25Gy for each VMAT method across the three patient cohorts. In Group 1, the VMAT-2P technique recorded the highest mean heart dose at 5·00 Gy (with a range of 3·27–6·55 Gy), followed by VMAT-4P at 4·71 Gy (range: 3·14–6·17 Gy) and VMAT-5P at 4·40 Gy (range: 3·16–5·98 Gy). The heart V5Gy was also greatest for VMAT-2P at 23·82% (range: 14·22–34·02%), while VMAT-4P and VMAT-5P recorded 21·00% (range: 13·00–30·33%) and 19·61% (range: 12·51–29·87%), respectively. The heart V25Gy values were

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(a)

```python
# import required Python libraries
import numpy as np
import pandas as pd
from sklearn.linear_model import ElasticNet
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error, median_absolute_error
```

```python
df = pd.read_csv("https://raw.githubusercontent.com/rishiraj-cs/TumorDose/main/HEART_MeanDose_2P.csv")

df = df.drop(df.columns[:3], axis=1)

print("Shape of dataframe df: {}".format(df.shape))

X = df.iloc[:,0:4].values

y = df.iloc[:,-1].values

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.3,random_state = 0)

print("Shape of dataframe X_train: {}".format(X_train.shape))
print("Shape of dataframe y_train: {}".format(y_train.shape))

print("Shape of dataframe X_test: {}".format(X_test.shape))
print("Shape of dataframe y_test: {}".format(y_test.shape))
```

```
Shape of dataframe df: (53, 5)
Shape of dataframe X_train: (37, 4)
Shape of dataframe y_train: (37,)
Shape of dataframe X_test: (16, 4)
Shape of dataframe y_test: (16,)
```

(b)

```python
# Define the model
model = ElasticNet()

# Train and evaluate the model
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

rmse = np.sqrt(mean_squared_error(y_test, y_pred))
medae = median_absolute_error(y_test, y_pred)

print(f"ElasticNet Regression Results:")
print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
print(f"Median Absolute Error (MEDAE): {medae:.2f}")
```

```
ElasticNet Regression Results:
Root Mean Squared Error (RMSE): 0.92
Median Absolute Error (MEDAE): 0.59
```

(c)

```python
[61] # Extract feature importance
feature_importance = np.abs(model.coef_)
feature_names = df.columns[:-1]  # Exclude the target variable
feature_importance_df = pd.DataFrame({'Feature': feature_names, 'Importance': feature_importance})
feature_importance_df = feature_importance_df.sort_values('Importance', ascending=False)
print(feature_importance_df)
```

```
        Feature  Importance
0       MHD(CM)    0.332911
1       THV(cc)    0.078725
2  HEART VOLUME    0.019211
3    PTV VOLUME    0.015269
```

Figure 3. (a) Importing the required libraries and preparing the dataset, and (b) Training and Evaluation of the ElasticNet regression model. (c) Feature Importance of various anatomical features in predicting Mean Dose using ElasticNet regression model.

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Table 1. Patient groups and heart anatomical parameters

Group (Range)	No. of Patients	MHD (cm)	THV (cc)	HV (cc)	PTVV (cc)
1	12	1·4–2·25	17·1–36·8	300–430·0	300–550
2	20	2·3–2·89	36·9–64·4	430·1–510	550·1–700
3	21	2·9–4	64·5–125	510·1–725	700·1–1190·1

MHD, maximum heart distance (cm); THV, tangent heart volume in field (cc); HV, heart volume (cc); PTV, planning target volume (cc).

Table 2. Heart dosimetric parameters by different volumetric modulated arc therapy (VMAT) techniques

Group (Range)	VMAT Techniques	Heart Mean Dose (Gy) Avg. (Min.–Max.)	Heart V5Gy (%) Avg. (Min.–Max.)	Heart V25Gy (%) Avg. (Min.–Max.)
1	VMAT-2P	5·00 (3·27–6·55)	23·82 (14·22–34·02)	2·70 (0·33–6·00)
	VMAT-4P	4·71 (3·14–6·17)	21·00 (13·00–30·33)	2·71 (0·06–6·01)
	VMAT-5P	4·40 (3·16–5·98)	19·61 (12·51–29·87)	2·81 (0·05–6·24)
2	VMAT-2P	5·70 (3·84–7·47)	26·13 (14·72–40·65)	4·28 (1·43–8·82)
	VMAT-4P	5·31 (3·54–7·07)	22·59 (12·77–32·66)	3·43 (1·17–8·70)
	VMAT-5P	5·08 (3·27–7·19)	21·56 (11·44–37·11)	4·41 (1·15–9·09)
3	VMAT-2P	6·24 (3·89–8·85)	29·70 (14·35–53·78)	5·27 (1·51–9·35)
	VMAT-4P	5·69 (3·48–7·14)	24·04 (12·20–35·79)	5·22 (1·53–9·30)
	VMAT-5P	5·57 (3·72–7·66)	23·03 (13·40–37·59)	5·60 (1·74–9·96)

VMAT, volumetric modulated arc therapy; 2P,4P,5P, partial arcs.

Table 3. Elastic Net regression model to predict heart doses for the performance of three volumetric modulated arc therapy (VMAT) techniques

	VMAT 2P		VMAT 4P		VMAT 5P	
Heart Parameters	RMSE	MedianAE	RMSE	MedianAE	RMSE	MedianAE
MEAN DOSE (Gy)	0·9180840719	0·5926458332	0·9099624084	0·5760808472	1·081165994	0·7508545
V5Gy (%)	7·971793505	5·570206228	5·999036149	4·798075169	4·824229404	2·118848501
V25Gy(%)	2·147328691	1·005335023	2·179816114	1·531300543	2·538276043	2·123246959

RMSE, root mean square error; MedianAE, median absolute error.

comparable across all three techniques, falling within the range of 2·70–2·81%.

In Group 2, the VMAT-2P technique exhibited the highest mean heart dose at 5·70 Gy (with a range of 3·84–7·47 Gy), followed closely by VMAT-4P at 5·31 Gy (range: 3·54–7·07 Gy) and VMAT-5P at 5·08 Gy (range: 3·27–7·19 Gy). The heart V5Gy was also greatest for VMAT-2P, recorded at 26·13% (range: 14·72–40·65%), while VMAT-4P and VMAT-5P showed values of 22·59% (range: 12·77–32·66%) and 21·56% (range: 11·44–37·11%), respectively. The heart V25Gy values varied between 3·43% and 4·41% across the three techniques.

In Group 3, the VMAT-2P technique recorded the highest mean heart dose at 6·24 Gy (with a range of 3·89–8·85 Gy). This was followed by VMAT-4P, which delivered a mean dose of 5·69 Gy (range: 3·48–7·14 Gy), and VMAT-5P, with a mean dose of 5·57 Gy (range: 3·72–7·66 Gy). The heart V5Gy was also greatest for VMAT-2P at 29·70% (range: 14·35–53·78%), while VMAT-4P and VMAT-5P had heart V5Gy values of 24·04% (range: 12·20–35·79%) and 23·03% (range: 13·40–37·59%), respectively. The heart V25Gy values varied between 5·22% and 5·60% across the three techniques.

Predictive model

We employed the Elastic Net regression model to predict heart doses for the performance of three VMAT techniques (2P, 4P and 5P) was evaluated using RMSE, Median and absolute error (AE) for mean dose, V5Gy and V25Gy. The results are as demonstrated in Table 3.

In terms of mean dose, VMAT-4P achieved the lowest RMSE of 0·9099 and a MEDAE of 0·5760, indicating its potential for the most precise dose prediction among the three methods evaluated. Regarding V5Gy, VMAT-5P outperformed the others with the lowest RMSE of 4·8242 and a MEDAE of 2·1188, suggesting its effectiveness in predicting and reducing the volume of tissue exposed to low doses. For V25Gy, VMAT-2P recorded the lowest MEDAE at 1·0053, while VMAT-4P demonstrated a marginally lower RMSE of 2·1798 compared to VMAT-2P is 2·1473.

Discussion

Our study was designed to assess the impact of various VMAT techniques on heart dose parameters in patients with left-sided

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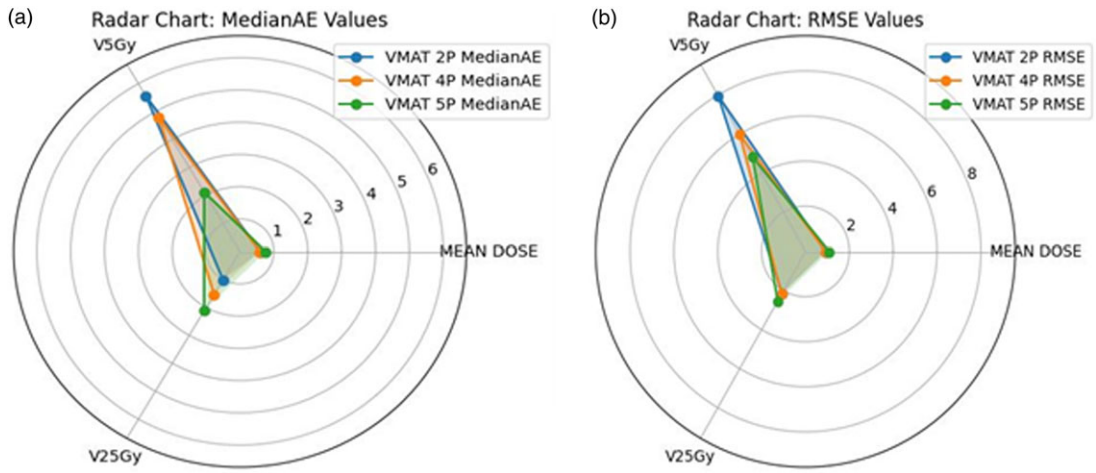

Figure 4. (a) & (b) radar chart across three VMAT techniques in Elastic Net regression models.

breast cancer, considering different anatomical parameters. Additionally, we evaluated the predictive capabilities of Elastic Net regression models for heart dose metrics. The findings provide essential insights into the relationship between patient anatomy, the choice of VMAT techniques and cardiac exposure during RT.

Patient anatomy and VMAT technique effectiveness

Organising patients into three categories based on increasing heart anatomical parameters revealed a notable trend: heart doses generally escalated from Group 1 to Group 3 across all VMAT techniques, as shown in Tables 1 and 2. This link between larger heart volumes, increased MHDs and heightened cardiac exposure underscores the importance of factoring in individual patient anatomy during treatment planning.

Notably, our study findings revelled that VMAT-5P typically resulted in the lowest average heart doses, especially in patients with smaller MHDs. However, its advantages were not as significant for patients with larger MHDs and more intricate anatomical parameters. It is important to note that V25Gy did not always correspond with the mean heart dose, underscoring the need to evaluate a range of dosimetric factors.

These results imply that treatment planners should take into account MHD, THV, HV and PTV when determining the most appropriate VMAT technique. While VMAT-5P may be optimal for patients with favourable anatomical features, the decision between VMAT-4P and VMAT-5P for those with larger MHDs should be based on specific dosimetric objectives and individual patient characteristics.

A previous study[24,25] has predominantly utilised MHD as the main predictor for heart dosimetry in tangential field RT for left-sided breast cancer. Our research, however, proposes that a more integrated approach is necessary. This approach should take into account various parameters, such as MHD, THV within the field, heart volume (HV) and PTV, to select the most appropriate VMAT technique, ensuring optimal heart dosimetry.

Predictive modelling and feature importance

The Elastic Net regression models yielded encouraging findings in the prediction of heart dose metrics for VMAT techniques as demonstrated in Table 3. For mean heart dose, the models displayed consistent performance, with RMSE values ranging from 0·91 to 1·08 Gy. Interestingly, the model's accuracy in predicting V5Gy improved with incresing arc in VMAT techniques complexity, suggesting that advanced techniques provide more reliable low-dose distribution predictions demonstrated in Fig. 4(a) and 4(b) showed that the radar chart indicates that the 5P plan tends to outperform the others, particularly in terms of lowering the mean dose and V25Gy, while achieving comparable V5Gy coverage. This suggests that the 5P VMAT plan may offer a superior dose distribution advantage.

Fig. 5 demonstrates that feature importance analysis has identified MHD as the most significant factor, contributing nearly 74% to the model's predictive accuracy. This finding is consistent with prior studies[24,25] that have recognised the importance of MHD in treatment planning. Our analysis further indicated that THV, HV and PTVV also significantly impact the model's decision-making, with THV being the second most influential factor at approximately 18% and HV at about 4%. The incorporation of PTV Volume as a predictive variable is significant, despite its lower importance approx. 3%. Although previous study[26,27] emphasised the importance of target volume in estimating heart dose, our results indicate that its impact may be less significant compared to heart-specific metrics. These results suggest that while MHD is a dominant factor, it is important to consider other parameters when choosing a VMAT technique.

Our investigation shows that Elastic Net regression models are proficient in predicting heart dose metrics for VMAT techniques. The three-fold cross-validation results affirm the models' strength, with RMSE values recorded between 0·91 and 1·08 Gy for mean heart dose, 4·82 to 5·23 Gy for V5Gy and 2·14 to 2·25 Gy for V25Gy. These findings indicate that the models can be utilised to predict heart dose metrics for VMAT techniques with considerable accuracy.

Our study findings reveal that each VMAT technique possesses distinct advantages and disadvantages regarding dosimetric accuracy. VMAT-4P exhibited the lowest RMSE and MEDAE for mean dose, indicating its potential for the most accurate dose prediction among the three techniques assessed. Conversely, VMAT-5P excelled in minimising the volume of tissue receiving low doses (V5Gy), achieving the lowest RMSE and MEDAE. For the V25Gy metric, VMAT-2P showed the lowest MEDAE, while VMAT-4P had a slightly lower RMSE than VMAT-2P. These results suggest that the selection of a VMAT technique should be tailored to specific dosimetric goals and the unique characteristics of each patient.

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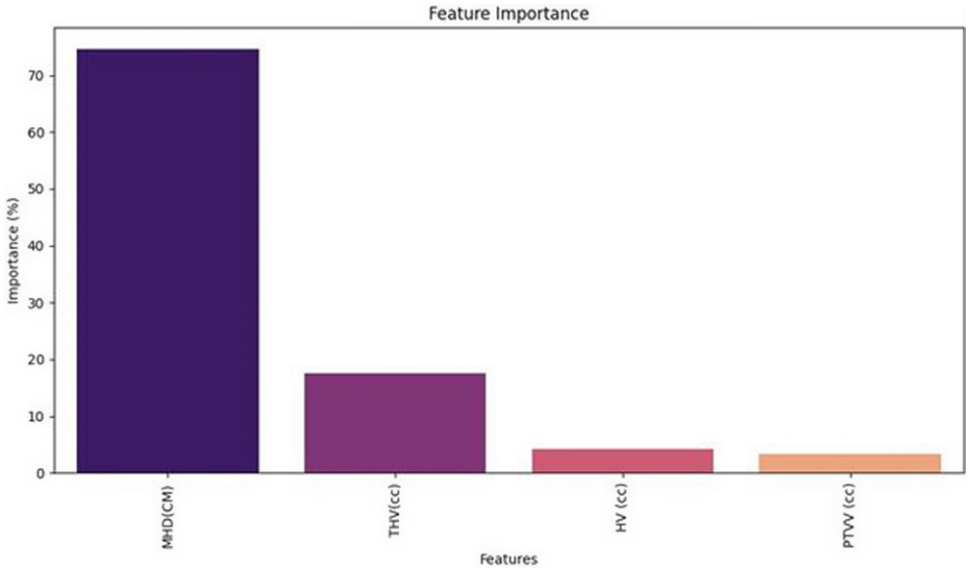

Figure 5. Demonstrated feature importance of anatomical parameters.

The findings of our research present three key implications. First, treatment planners are encouraged to take into account various anatomical parameters, such as MHD, THV, HV and PTV, when selecting the most suitable VMAT technique for patients with left-sided breast cancer. Second, the choice of VMAT technique should align with specific dosimetric goals, including mean dose, V5Gy or V25Gy. Lastly, our research underscores the importance of a deeper comprehension of the connections between patient anatomy, the effectiveness of VMAT techniques and dosimetric precision. By understanding the interactions among these elements, treatment planners can create more effective and tailored treatment approaches.

Compared to earlier ML models, our Elastic Net regression models exhibited superior performance in forecasting heart dose metrics. A study conducted by Wang et al.[28] utilised a random forest model for heart dose prediction, yielding a RMSE of 1·23 Gy. In contrast, our Elastic Net models achieved an RMSE between 0·91 and 1·08 Gy, demonstrating a notable improvement in predictive accuracy for heart dose estimation. This aligns with Li et al.[29] study that has demonstrated the efficacy of Elastic Net regression in forecasting radiation doses to at-risk organs. Additionally, our models highlighted MHD as the most critical predictor of heart dose, which is consistent with the findings of Darby et al.[30] and Ranger et al.,[31] who also underscored the importance of MHD in optimising heart protection during RT.

Treatment planning considerations

The findings of this study carry important implications for the formulation of more effective and customised treatment approaches for patients with left-sided breast cancer. By understanding the relationship between patient anatomy, the efficacy of VMAT techniques, and the precision of dosimetric measurements, treatment planners can enhance their decision-making processes. The predictive models established here can act as essential resources for rapidly assessing heart dose metrics, which may facilitate a more efficient treatment planning workflow.

Limitation of study and future consideration

This study has several limitations, notably the small sample size of 53 patients, which may restrict the applicability of the findings. The evaluation was limited to only three VMAT techniques, and important confounding factors such as patient age, tumour location and treatment planning parameters were not included in the analysis. Future investigations should aim for larger patient populations, examine a wider variety of VMAT techniques and take into account a more comprehensive set of variables that could affect heart dose metrics. Additionally, prospective studies are needed to validate the predictive models in clinical settings and assess their influence on treatment outcomes.

Conclusion

This study investigation highlights the essential aspects of patient anatomy, the effectiveness of VMAT techniques and the accuracy of dosimetric evaluations in the context of treatment planning for left-sided breast cancer. The findings indicate that Elastic Net regression models can reliably predict heart dose metrics for different VMAT approaches, thereby supporting tailored treatment planning. It is vital to consider multiple anatomical factors, including MHD, THV, HV and PTV, when selecting VMAT techniques, as each option carries its own set of dosimetric pros and cons. Future research should focus on validating these insights in larger patient populations and exploring the integration of predictive models into automated planning systems to enhance treatment outcomes and lower the risk of cardiac toxicity.

Data Availability Statement. The data underlying the findings of this study can be obtained from the corresponding author (M.Z.) upon a reasonable request.

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Declaration. The research is of a retrospective design and was carried out with the endorsement of the department's research committee.

Informed Consent Statement. In this study, patient-informed consent forms were not necessary because they utilised clinical data retrospectively for research and educational objectives.

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