

# Prediction of Multileaf Collimator Leaf Positions Using a Hybrid BKA– Neural Network Model for Radiotherapy Delivery Accuracy

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## Research Article

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# Prediction of Multileaf Collimator Leaf Positions Using a Hybrid

## BKA–Neural Network Model for Radiotherapy Delivery Accuracy

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### Abstract

**Methods:** The Black-winged Kite Algorithm (BKA) was integrated with a three-layer BP Neural Network (BKA-BPNN), where BKA optimized the initial weights and thresholds. Thirteen dosimetric and mechanical parameters were extracted from the treatment planning log files as inputs to the model, with the delivered leaf positions serving as the target response. The model's performance was evaluated using various metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), regression plots, and error histograms.

**Results:** The improved neural network model (BKA-BPNN) accurately predicted MLC leaf

positions, demonstrating superior performance ( $MAE = 0.0026 \text{ mm}$ ,  $MSE = 0.00001 \text{ mm}^2$ ). A correlation coefficient of 0.9999 indicates a high correlation between the predicted and actual leaf positions. Additionally, the prediction efficiency has significantly improved. Compared with the traditional BPNN model, the BKA-BPNN model reduces the MAE by 89.21%. When compared with the improved Particle Swarm Optimization Back Propagation Neural Network (PSO-BPNN) model, it achieves a 39.53% reduction in MAE.

**Conclusion:** The proposed BKA-BPNN model outperforms both conventional neural networks and deep learning-based neural networks in prediction accuracy, which possesses great application potential for boosting the precision of radiotherapy treatment.

**Key words:** radiation therapy, multi-leaf collimator, black-winged kite algorithm, artificial intelligence, prediction of position, KylinRay-MELAC

## 1 Introduction

Over the past few decades, significant progress has been made in radiotherapy techniques, particularly with the development of Intensity-Modulated Radiation Therapy (IMRT) and Volumetric Modulated Arc Therapy (VMAT). The Multi-Leaf Collimator (MLC) represents an essential technological innovation that has emerged alongside these advancements in radiation treatment modalities.<sup>[1, 2]</sup> These advanced treatment techniques leverage the dynamic functionality of MLC systems to optimize therapeutic dose delivery to malignant targets, with concurrent sparing of radiosensitive normal structures through precision beam modulation.<sup>[3-7]</sup> Nevertheless, the increased sophistication of these treatment modalities correspondingly heightens the risk of deviations emerging between planned and practically achieved dose distributions. Extensive research evidence<sup>[8-12]</sup> indicates that MLC positional errors may significantly compromise dose delivery accuracy to the intended treatment volumes.

For example, systematic 1 mm displacements of MLC leaves toward the isocenter led to an 8.7% mean dose reduction in the Planning Target Volume (PTV).<sup>[13]</sup> Clinical evidence demonstrates that leaf positioning inaccuracies of  $\pm 0.5 \text{ mm}$  can induce dose deviations exceeding 3% in VMAT plans,<sup>[14]</sup> while errors of 1 mm may lead to dose inaccuracies approximating 5% in dynamic IMRT delivery.<sup>[12, 15]</sup> An increase in system shift errors corresponded to a rise in PTV mean dose deviation.<sup>[16]</sup> These consistent observations highlight that dosimetric accuracy is

directly dependent on the precision of MLC positioning.

Machine Learning (ML) methods can be employed to predict MLC leaf positions prior to IMRT/VMAT delivery, enabling compensation for deviations between planned and actual positions. Carlson et al.<sup>[17]</sup> conducted a comprehensive evaluation of three machine learning methodologies-random forest regression, cubist modeling, and multivariate linear regression-for predicting MLC positional errors. Their results demonstrated that the ML approaches exhibited strong predictive performance for MLC leaf displacement, consequently enhancing dose distribution accuracy and achieving superior gamma index compliance rates. However, some studies suggest that Artificial Neural Networks (ANNs) achieve superior performance compared to conventional ML methods in various applications.<sup>[18, 19]</sup> Osman et al.<sup>[20]</sup> employed a Feedforward Neural Network (FNN) to predict MLC positional errors using Varian linear accelerator log data.

Existing neural network models in the literature are primarily suitable for predicting individual leaf positions, but demonstrate significantly reduced accuracy when predicting other sequentially numbered leaves. This approach requires training separate models for each leaf, resulting in low prediction efficiency and poor generalizability. This paper develops a novel BKA-BPNN approach, where a Backpropagation Neural Network (BPNN) is optimized by the Black-winged Kite Algorithm (BKA), for accurate leaf position prediction based on log records of Elekta Axesse Linac systems accelerator (Elekta AB, Stockholm, Sweden).

The linear accelerator features an Agility MLC with 160 independently controlled leaves. This arrangement generates treatment fields up to 40×40 cm<sup>2</sup> at isocenter, where individual leaves exhibit a projected width of 5 mm.

## 2 Materials and Methods

### 2.1 BKA-BPNN model

The Black-winged Kite Algorithm (BKA) is a nature-inspired metaheuristic optimization method that mimics the hunting behavior of black-winged kites.<sup>[21]</sup> Demonstrating robust global exploration capability and rapid convergence characteristics, this algorithm effectively prevents premature convergence to local optima, thereby enhancing both precision and efficiency in

optimization processes.

This study integrates BKA with BPNN, leveraging BKA's global search capability and adaptive characteristics to dynamically optimize BP network parameters including learning rates and weight coefficients, thereby enhancing neural model performance. The optimization process is illustrated in Figure 1.

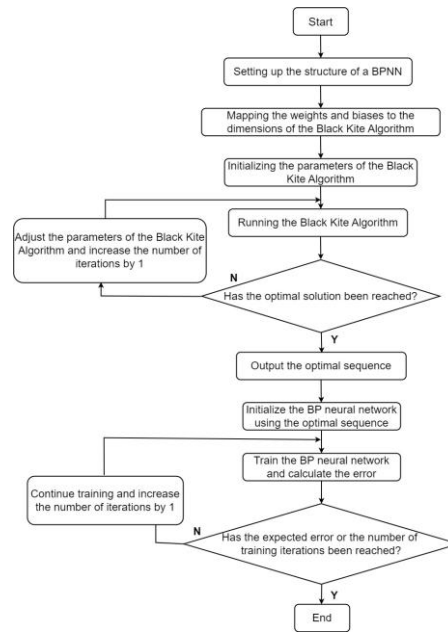


Figure 1. Flowchart of the BKA-BPNN

The proposed methodology comprises six key phases.

- (1) First, the baseline BPNN architecture is constructed by specifying the number of hidden layers and all structural parameters except connection weights and node thresholds, which are reserved for optimization.
- (2) In the BKA framework, each dimension corresponds to a weight or threshold parameter, with individual black-winged kite representing complete sets of network parameters as candidate solutions.
- (3) The algorithm initialization involves configuring population size, maximum iterations, and search space boundaries, with random position generation ensuring comprehensive exploration.
- (4) During execution, the BKA iteratively updates black-winged kite positions through simulated hunting behaviors while evaluating solution fitness using network performance metrics. The optimization continues until meeting termination criteria or the maximum

number of iterations is reached, thereby yielding the optimal solution.

(5) The ideal weights and thresholds obtained by the BKA algorithm are utilized to initialize the parameters of the BPNN, thereby enhancing the efficiency and performance of the training process through optimized initial configurations.

(6) Finally, the initialized BPNN will commence training until either the predefined error threshold is reached or the maximum number of training iterations is completed.

The parameter settings of the BKA are presented in Table 1.

Table 1. Parameters of the BKA

| Parameters              | Value |
|-------------------------|-------|
| Population size         | 300   |
| Predation coefficient   | 0.5   |
| Exploration coefficient | 1.2   |
| Space dimension         | 451   |
| Maximum iterations      | 20    |

The models employ 13 log-derived feature parameters as inputs, which are mapped to 13 input layer neurons. Determining the number of hidden layer neurons is a critical design factor: too few neurons may result in underfitting, while too many can increase computational costs and the likelihood of overfitting. After evaluating model performance and training efficiency, the hidden layer was set to 30 neurons. Leaf position prediction is mapped to one output neuron. The hidden layer employs a hyperbolic tangent sigmoid activation function, while the output layer utilizes a linear transfer function. MATLAB 2019a (MathWorks, Natick, Massachusetts, USA) was employed for constructing the BKA-BPNN model.

## 2.2 Data materials

Fifty IMRT treatment plans were randomly sampled, covering three anatomical sites in equal proportions: 17 plans for the head and neck, 17 plans for the chest, and 16 plans for the abdomen. All plans were generated using the Monaco treatment planning system (TPS v5.11.03) with 6 MV photon beams. The Elekta Linac's DynaLog system acquired mechanical and beam delivery parameters at 25 Hz during irradiation, capturing both actual delivery data and planned TPS values. The data are synchronized to accurately record discrepancies for each parameter.

The archived log files are stored in binary format with the trf (treatment record file) extension, which does not support direct extraction of sampled data points. A Python algorithm was developed for log file format conversion to enable direct extraction of sampling point data.

### 2.3 Predictive parameters

The following parameters extracted from parsed log files are considered as predictive factors for determining delivered MLC leaf positions: dose fraction, gantry angle, collimator angle,  $X_1$  and  $X_2$  jaw positions,  $Y_1$  and  $Y_2$  carriage positions, planned leaf positions, adjacent leaf positions, leaf gap, leaf velocity, and leaf acceleration (see Table 2).<sup>[22-28]</sup>

### 2.4 Model training, validation, and testing

Previous research has demonstrated that the data partitioning scheme of 70% for training, 15% for validation, and 15% for testing outperforms alternative allocations (e.g., 60%-20%-20%) and is widely adopted in machine learning model development.<sup>[20]</sup> Accordingly, this study employed the 70%-15%-15% split ratio for randomized data division. The BKA-BPNN model generated leaf position predictions, which were subsequently evaluated against the corresponding delivered positions. Model performance was quantified through multiple measures comprising mean absolute error (MAE), mean squared error (MSE), error distribution histograms, and regression analysis plots to determine prediction accuracy and reliability.

Table 2. Predictive input parameters

| No. | Predictive parameters         | Formula |
|-----|-------------------------------|---------|
| 1   | dose fraction                 | -       |
| 2   | gantry angle                  | -       |
| 3   | collimator angle              | -       |
| 4   | $X_1$ jaw positions           | -       |
| 5   | $X_2$ jaw positions           | -       |
| 6   | $Y_1$ carriage positions      | -       |
| 7   | $Y_2$ carriage positions      | -       |
| 8   | planned leaf positions        | -       |
| 9   | adjacent left leaf positions  | -       |
| 10  | adjacent right leaf positions | -       |

|    |                   |                                   |
|----|-------------------|-----------------------------------|
| 11 | leaf gap          | $\text{abs}(p_l - p_r)$           |
| 12 | leaf velocity     | $\frac{p_i - p_{i-1}}{t_i(0.04)}$ |
| 13 | leaf acceleration | $\frac{v_i - v_{i-1}}{t_i(0.04)}$ |

Note: Subscripts  $l$  and  $r$  indicate left/right leaf positions ( $p_l$ ,  $p_r$ ); and  $i$  and  $i-1$  denote current/previous sampling points for position (p) and velocity (v); and  $t_i$  represents the time interval between sampling points.

### 3 Results

#### 3.1 Model performance

As illustrated in Figure 2(a), the MSE of individual leaves during training, validation, and testing phases demonstrated rapid decline in the training process. The MSE reached  $1 \times 10^{-5}$  mm<sup>2</sup> after merely 9 iterations and remained stable upon convergence. The close alignment between validation/test MSE values and training MSE indicates no occurrence of overfitting in the model. The model achieved low MSE values, demonstrating its superior predictive accuracy. Figure 2(b) shows the MSE of the standard BPNN. By comparing these two graphs, it can be clearly observed that the BKA-BPNN has a faster convergence speed in the initial stage of training and can achieve a better training effect within a relatively short period of time (the BPNN model reaches  $1 \times 10^{-5}$  mm<sup>2</sup> after 38 iterations).

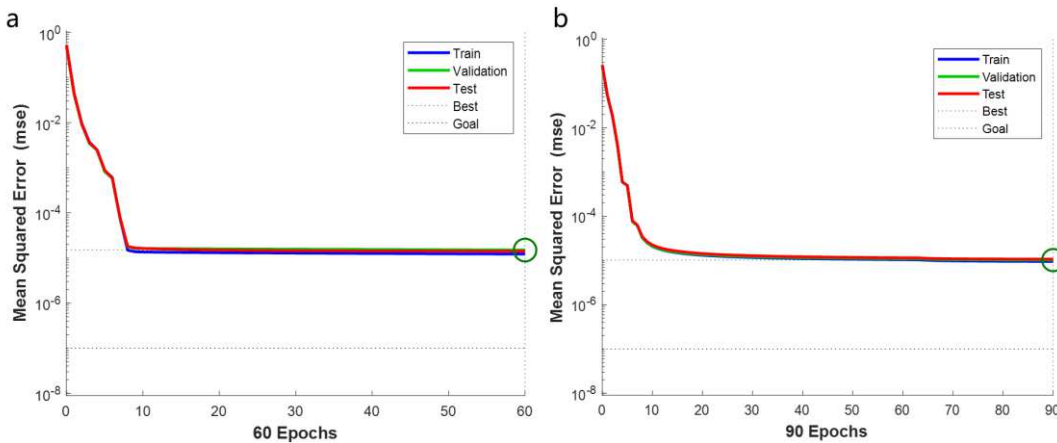
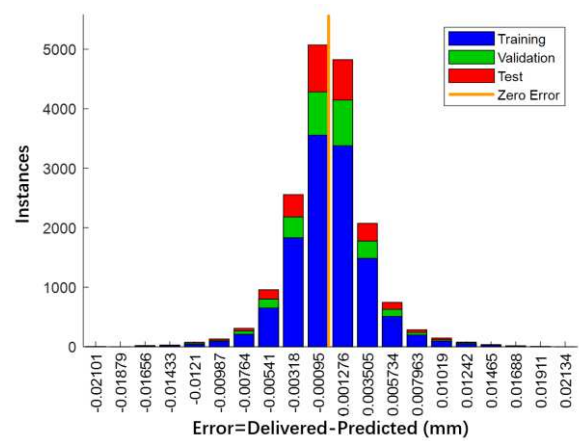


Figure 2. Mean squared error (a) MSE of the BKA-BPNN (b) MSE of the BPNN

The error histogram serves as an additional performance evaluation metric, as illustrated in Figure 3. The distribution demonstrates that most of the errors are close to zero, and only a very small number of errors deviate far from zero. The data exhibits quasi-Gaussian characteristics, peaking around zero, indicating strong agreement between predicted and actual delivered

167 values.



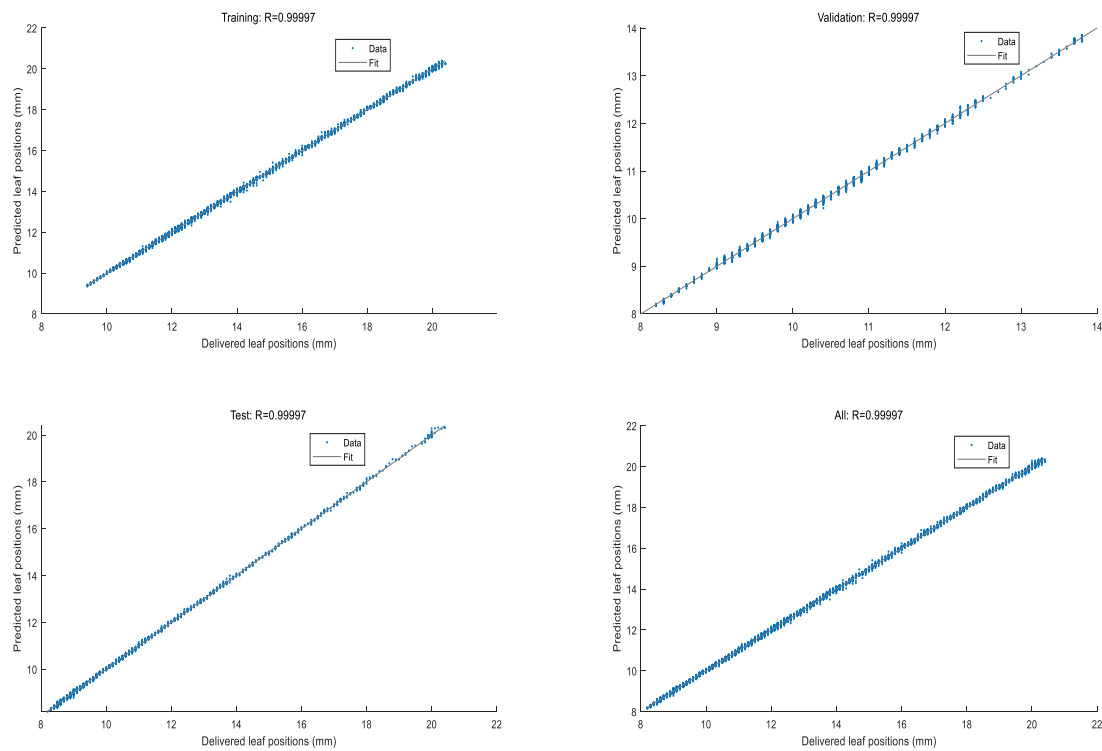
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Figure 3. Error histogram

170 Figure 4 presents the regression plots between delivered and predicted leaf positions, which  
171 demonstrate the neural network's fitting performance to the data. All data points are tightly  
172 clustered along the diagonal line, with a correlation coefficient  $R$  approaching 1 ( $R=0.9999$ ),  
173 indicating the BKA-BPNN's high precision in leaf position prediction, with results nearly  
174 identical to the delivered positions.

175



176

177

Figure 4. Regression plots

### 3.2 Prediction results

The prediction results of leaf positions by the BKA-BPNN model are presented in Figure 5, demonstrating close agreement between predicted and delivered leaf positions.

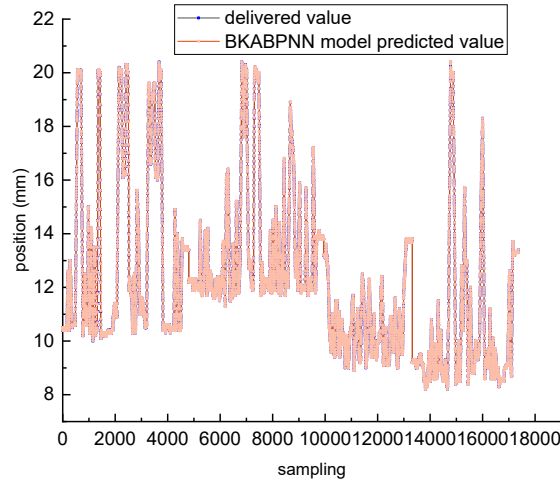


Figure 5. BKA-BPNN prediction results

Figure 6(a) illustrates the positional deviations between planned and delivered MLC leaf positions during radiotherapy delivery, while Figure 6(b) demonstrates the discrepancies between delivered positions and predicted positions.

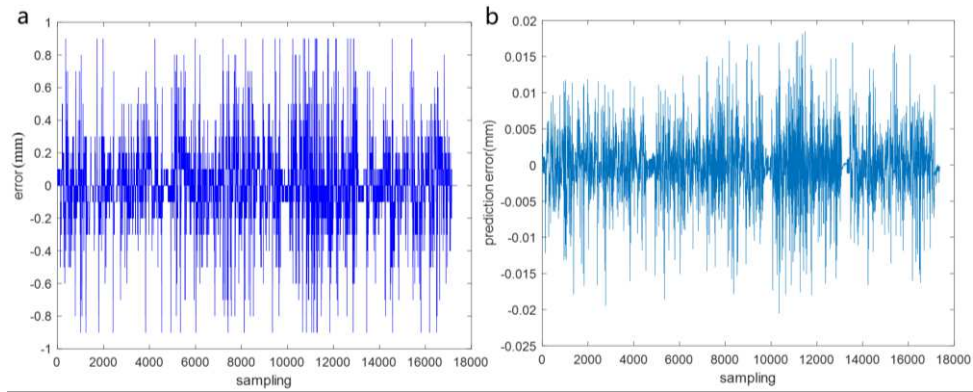


Figure 6. Position error (a) error between planned and delivered positions (b) error between delivered and predicted positions

As shown in Figure 6(a), the maximum deviation between planned and delivered leaf positions prior to prediction was 0.9 mm, which significantly impacts dose distribution in radiation therapy. In contrast, Figure 6(b) demonstrates that the predicted values from the BKA-BPNN model exhibit near-perfect agreement with delivered leaf positions, with a maximum prediction error of only 0.021 mm. This indicates that the model achieves high predictive accuracy and can effectively mitigate dose discrepancies caused by leaf position deviations, thereby

enhancing the precision of radiation therapy delivery.

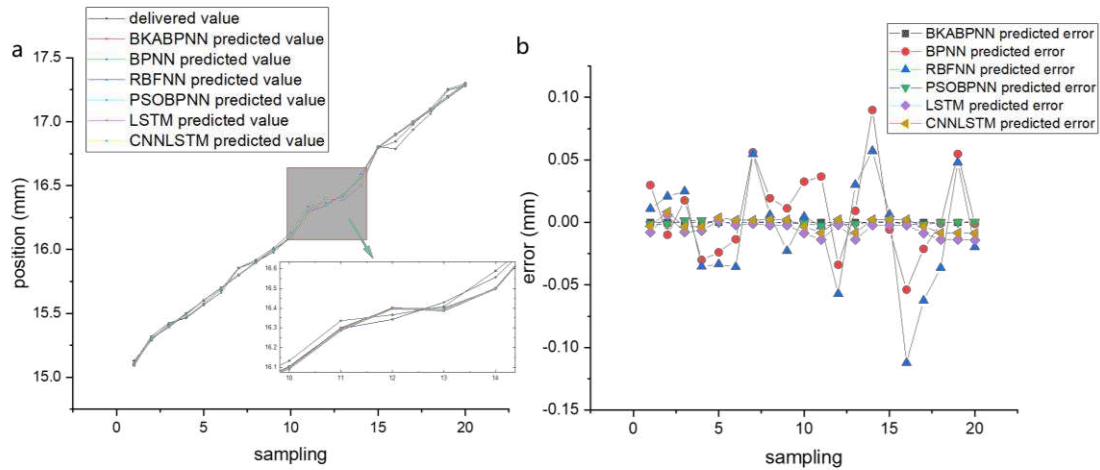


Figure 7. Comparative of model predictions (a) predicted positions (b) prediction errors

BPNN, Radial Basis Function Neural Network (RBFNN), Particle Swarm Optimization-Backpropagation Neural Network (PSO-BPNN), Long Short-Term Memory Neural Network (LSTM), and Convolutional Neural Network-LSTM Neural Network (CNN-LSTM) were developed for MLC position prediction. The comparative prediction results are presented in Figure 7 and table 3.

As observed in Figure 7(a), the predicted values (red line) from the BKA-BPNN model demonstrate high consistency with the delivered values (gray line), indicating that the BKA-BPNN model achieves exceptional accuracy in position prediction. Compared with other models, the BKA-BPNN exhibits more stable and accurate predictive performance across multiple sampling points.

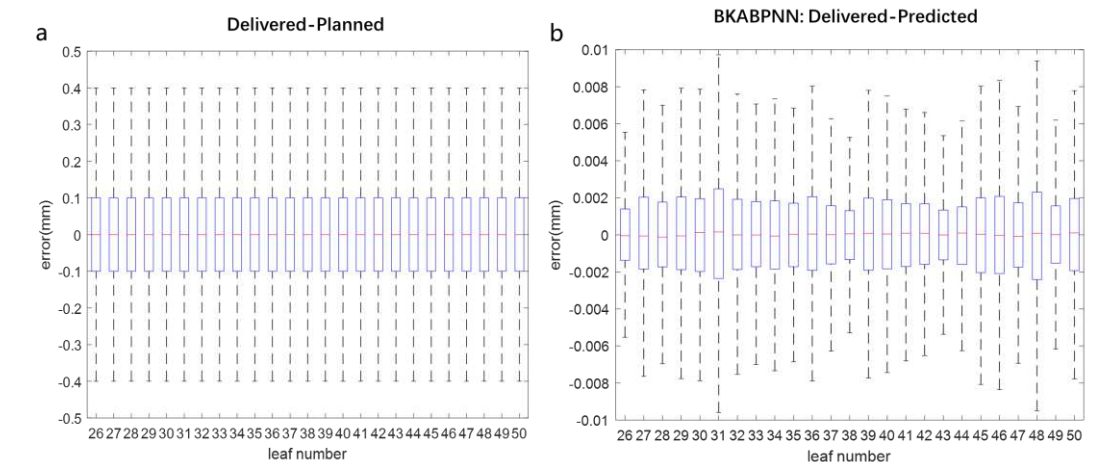
Figure 7(b) presents the prediction errors of different models. Error control is crucial for model reliability. The results show that the errors of the BKA-BPNN model (gray squares) remain close to zero at most sampling points with minimal fluctuations, demonstrating its superior stability and high prediction accuracy. In contrast to the BPNN (red circles) and RBFNN (blue triangles), which exhibit significant deviation variations at certain sampling points, the BKA-BPNN model shows remarkable advantages.

Furthermore, as shown in Table 3, the BKA-BPNN model achieves the lowest MAE of 0.0026 mm among all models. A lower MAE indicates closer agreement between predicted and delivered values, and the superior MAE performance of the BKA-BPNN model further confirms its advantage in MLC position prediction accuracy.

Table 3. Model prediction results

| Model    | MAE(mm) | MSE(mm <sup>2</sup> ) | Time(s) |
|----------|---------|-----------------------|---------|
| BKA-BPNN | 0.0026  | 0.00001               | 57      |
| PSO-BPNN | 0.0043  | 0.00003               | 2114    |
| BPNN     | 0.0241  | 0.0010                | 98      |
| RBFNN    | 0.0331  | 0.0019                | 127     |
| LSTM     | 0.0078  | 0.0001                | 878     |
| CNN-LSTM | 0.0068  | 0.00008               | 1007    |

219 Additionally, the BKA-BPNN model demonstrates the smallest MSE (0.00001 mm<sup>2</sup>) among all  
220 evaluated models. Since a smaller MSE indicates better predictive performance, this result  
221 provides further evidence of the model’s high-precision prediction capability.  
222 The BKA-BPNN model requires a computation time of 57 s, demonstrating significantly higher  
223 computational efficiency compared to other models, including the PSO-BPNN (2114 s) and  
224 CNN-LSTM Neural Network (1007 s).  
225 Figure 8 presents a boxplot illustrating the positional deviations between delivered and planned  
226 positions, as well as between delivered and predicted positions, for leaf numbers 26 through 50.  
227 The BKA-BPNN model exhibits significantly lower prediction errors for leaves with varying  
228 sequence numbers compared to the positional deviations between delivered and planned  
229 positions, demonstrating its superior applicability for positional prediction of leaves across  
230 different sequence numbers.



232 Figure 8. Leaves positional errors (a) errors between planned and delivered leaf positions (b)

the BKA-BPNN model prediction errors

Figure 9 presents the evaluation metrics (MAE, MSE, RMSE) of the BPNN and BKA-BPNN models for predicting different leaf positions. The BPNN model exhibits significant fluctuations in prediction metrics when applied to leaf position prediction with different sequence numbers. This indicates its poor adaptability in handling varying leaf positions, necessitating individual model training for each specific leaf position. Such an approach not only increases computational complexity and time costs but also reduces the model's prediction efficiency and generalization capability.

In contrast, the BKA-BPNN model demonstrates smaller fluctuations and lower absolute values in prediction metrics across different leaf positions. This superior performance suggests that the BKA-BPNN model possesses higher universality and stability in processing diverse leaf positions, enabling direct prediction for other leaves without requiring retraining. These characteristics significantly enhance the efficiency of MLC position prediction while reducing the time required for model training and adjustment.

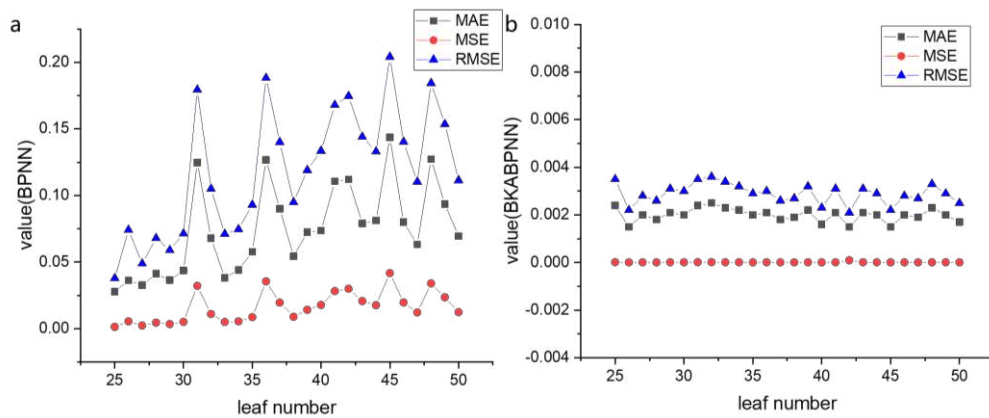


Figure 9. Prediction metrics for different leaf positions (a) prediction metrics of BPNN (b) prediction metrics of BKA-BPNN

Figure 10 presents the MLC leaf position prediction results of the BKA-BPNN model for the KylinRay-MELAC accelerator (Figure 11).

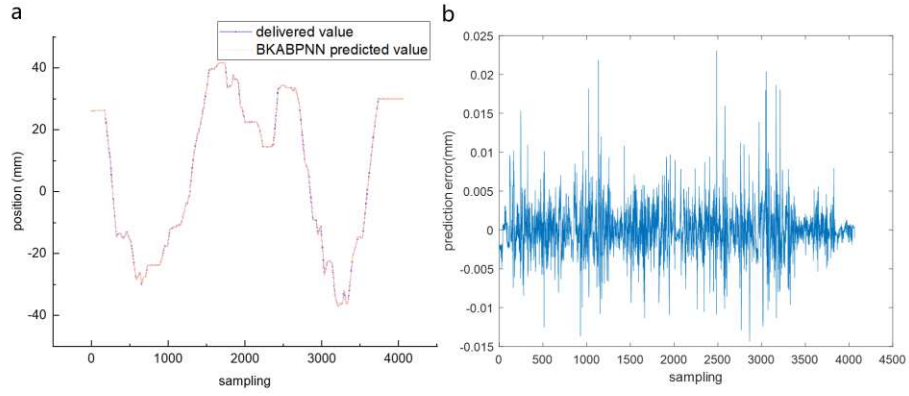


Figure 10. Prediction results (a) predicted positions (b) prediction errors

The results demonstrate that the BKA-BPNN model achieves high prediction accuracy, further confirming its strong generalization capability.



Figure 11. KylinRay-MELAC accelerator

## 4 Discussion

The positional accuracy of MLC leaves is critical for dose delivery accuracy in radiation therapy. Budgell et al.<sup>[29]</sup> demonstrated that achieving dosimetric precision in dynamic IMRT necessitates MLC positioning tolerances tighter than the 1 mm standard (AAPM TG-142).<sup>[30]</sup> Studies<sup>[12, 31, 32]</sup> have demonstrated a dose-dependent relationship between MLC positioning errors and delivery accuracy in radiation therapy, where greater leaf displacement correlates with increased dose deviations. Accordingly, high-precision MLC leaf positioning is crucial. In this study, the BKA-BPNN models were established to predict MLC leaf positions in radiation therapy, utilizing log file data. The parameters extracted and calculated from log file data in Table 2 demonstrate significant predictive relevance for MLC leaf positioning, thereby enhancing prediction accuracy while reducing training time and computational resource consumption. As evidenced by the experimental results presented in Figures 2-4, the novel

BKA-BPNN architecture demonstrates superior performance in the prediction of the MLC position, being capable of achieving high-precision prediction.

The BKA-BPNN model achieved the lowest MAE (0.0026 mm) and MSE (0.00001 mm<sup>2</sup>) among all comparative models. Compared with the conventional BPNN model, the BKA-BPNN model demonstrated an 89.21% reduction in MAE and a 41.84% improvement in prediction efficiency. When compared with the improved PSO-BPNN model, it showed a 39.53% reduction in MAE. Previous studies have reported varying MAE values for t MLC position prediction models. Random forest models achieved MAEs of 0.124 mm, 0.089 mm, and 0.165 mm across three institutions, while linear regression yielded 0.134 mm, 0.086 mm, and 0.162 mm respectively<sup>[17]</sup>. ANN demonstrated an MAE of 0.24 mm<sup>[33]</sup>. Chuang et al.<sup>[34]</sup> stated that the MAE predicted by the boosted tree model amounted to 0.0065 mm. In a similar vein, Osman et al.<sup>[20]</sup> reported an MAE value of 0.006 mm. The proposed BKA-BPNN model not only attained the lowest MAE, a clear indication of its preeminent prediction accuracy, but also manifested robust generalizability in position prediction. This generalizability held across diverse leaf indices and different linear accelerators, highlighting the model's broad applicability and reliability in various scenarios within the domain of position prediction.

Agnew et al.<sup>[35, 36]</sup> utilized electronic portal imaging device (EPID) images to monitor MLC positional errors; however, this approach constitutes a post-treatment verification method that cannot facilitate preemptive corrections. The BKA-BPNN model enables pre-treatment prediction and correction. Given the stability characteristics of MLC positional deviations during radiation therapy and considering that the prediction accuracy of neural network models is constrained by target response ranges, significant randomness in MLC deviations would lead to model performance degradation, indicating potential MLC malfunctions requiring maintenance.

The sophisticated nature of VMAT may lead to delivery inaccuracies. Pretreatment patient-specific quality assurance (QA) procedures, including dosimetric validation, are therefore implemented to verify delivery precision. The BKA-BPNN model facilitates detection of MLC displacement errors, thereby optimizing QA outcomes while conserving temporal and resources.<sup>[33]</sup> Furthermore, these predictive outputs can be incorporated within TPS to enhance radiotherapy precision.<sup>[20]</sup>

However, this study has certain limitations. The current neural network predictions are based solely on data from two accelerators. Future research should expand the data collection scope to incorporate measurements from a wider variety of accelerators, with the aim of developing a more universal predictive model.

## Acknowledgements

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## 5 Conclusion

In this study, a novel neural network model was developed to predict MLC leaf positions. The BKA-BPNN model demonstrates outstanding performance in MLC position prediction accuracy, computational efficiency, generalizability, and stability. These characteristics confer significant advantages for MLC position prediction applications. This model provides reliable technical support for radiation therapy, facilitating improved efficiency in treatment planning and enhanced execution accuracy, thereby contributing to both treatment safety and therapeutic efficacy for patients.

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## Competing Interests

The authors declare that they have no conflict of interest for this work.

## Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Jun Lv, Liuli Chen, Pengcheng Long, Zhiqiang Zhu, Tao He, Wenbo Li and Bo Yang. The first draft of the manuscript was written by Jun Lv, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.