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Prediction of the individual multileaf collimator positional deviations during dynamic IMRT delivery *priori* with artificial neural network

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Purposes: Multileaf collimator (MLC) positional accuracy during dynamic intensity modulation radiotherapy (IMRT) delivery is crucial for safe and accurate patient treatment. The deviations of individual leaf positions from its intended positions can lead to errors in the dose delivered to the patient and hence may adversely affect the treatment outcome. In this study, we propose a state-of-the-art machine learning (ML) method based on an artificial neural network (ANN) for accurately predicting the MLC leaf positional deviations during the dynamic IMRT treatment delivery *priori* using log file data.
Methods: Data of ten patients treated with sliding window dynamic IMRT delivery were retrospectively retrieved from a single-institution database. The patients' plans were redelivered with no patient on the couch using a Varian linear accelerator equipped with a Millennium 120 HD MLC system. Then the machine recorded log files data, a total of over 400 files containing 360 800 control points, were collected. A total of 14 parameters were extracted from the planning data in the log files such as leaf planned positions, dose fraction, leaf velocity, leaf moving status, leaf gap, and others. Next, we developed a feed-forward ANN architecture mapping the input parameters with the output to predict the MLC leaf positional deviations during the delivery *priori*. The proposed model was trained on 70% of the total data using the delivered leaf positional data as a target response. The trained model was then validated and tested on 30% of the available data. The model accuracy was evaluated using the mean squared error (MSE), regression plot, and error histogram.
Results: The deviations between the individual MLC planned and delivered positions can reach up to a few millimeters, with a maximum deviation of 1.2 mm. The predicted leaf positions at control points closely matched the delivered positions for all MLC leaves during the treatment delivery. The ANN model achieved a maximum MSE of 0.0001 mm^2 (root MSE of 0.0097 mm) in predicting the leaf positions at control points of test data for each leaf. The correlation coefficient, that measures the goodness of fit, was perfect (R = 0.999) in all plots indicating an excellent agreement between the predicted and delivered MLC positions for the training, validation, and test data.
Conclusions: We successfully demonstrated a proposed ANN-based method capable of accurately predicting the individual MLC leaf positional deviations during the dynamic IMRT delivery *priori*. Our ML model based on ANN outperformed the reported accuracy in the literature of various ML models. The results of this study could be extended to actual application in the dose calculation/optimization, hence enhancing the gamma passing rate for patient-specific IMRT quality assurance.
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Key words: artificial neural network, log files, MLC positional deviations, radiation therapy, virtual IMRT plan QA

1. INTRODUCTION

Intensity-modulated radiation therapy (IMRT) and volumetric modulated arc therapy (VMAT) are complicated techniques for radiotherapy treatment delivery. The complexities of these techniques introduce many potential sources of error. As a result, patient-specific plan quality assurance (QA) and dosimetric verification are performed before the patient's treatment delivery to ensure that the created plan on the treatment planning system (TPS) will be safely delivered by the linear accelerator (Linac).

Dynamic IMRT is a method used to deliver intensity-modulated beams using a multileaf collimator (MLC) with the leaves in motion during radiation delivery. One form of dynamic IMRT is the sliding window technique, in which the window created by each opposing pair of leaves traverses across the tumor volume in one direction, while the beam is on.[1,2] Deviations of an individual MLC leaf positions during the treatment delivery from the planned positions can lead to errors in dose distributions in the patient. This is observed even though the Linac passes mechanical and dosimetric QA criteria of the AAPM TG-142 report[3] (±1 mm MLC positioning tolerance) or ESRTO guidelines[4] (±0.5 mm MLC positioning acceptance criterion). Many studies[5–11] indicated that the delivered dose to the planning target volume (PTV) and organs at risk (OARs) can be directly affected by errors in MLC positioning. For instance, an error in leaf positioning of 1 mm could lead to a dose error in PTV of about 6% in step-and-shoot[9] and 5% in dynamic[10,11] IMRT delivery. Therefore, some studies[12–14] proposed such modulation indices such as the modulation complexity score, plan-averaged beam area/irregularity/modulation, mean aperture area, and degree of beam modulation for each beam to score the accuracy of IMRT plans before they are delivered. However, these methods[12–14] are correlational and do not provide any information about how the dose distribution will be influenced by the errors. A linear relationship between the MLC leaf velocity and positional error was reported by some investigators.[7,15,16] Hence, constraining the leaf speed and millimeters traveled per leaf per monitor unit (MU) can help improve the accuracy of the IMRT treatment plan delivery.[15,17]

Advanced approaches using machine learning (ML) methods could be used for predicting the MLC leaf positional deviations during the IMRT/VMAT delivery *priori.* There are very few studies in the literature about the prediction of the MLC positional errors with ML methods. Carlson et al.[18] examined various ML models such as linear regression, random forest, and cubist to predict the MLC positional errors during VMAT delivery using log files data from multiple institutions and the impact of these errors on the QA and dosimetry results. The study results showed that leaf positional errors are predictable in an accurate manner with ML algorithms, with a positive impact on enhancing the gamma passing rates for patient-specific QA and consequently reducing errors in delivered doses. ML models were also used in predicting the patient-specific IMRT/VMAT QA, by predicting the gamma passing rate.[19–26] Some recently published studies[19–26] investigated the feasibility of Poisson regression with LASSO regularization,[19–21] deep learning based on convolutional neural networks (CNN),[22–24] ensemble learning based on decision-tree,[25] random forest,[21] and support vector machine[26] ML models. All these proposed ML-based models demonstrated a capability in accurately predicting the IMRT/VMAT QA gamma passing rates. These studies were carried out for patient-specific IMRT/VMAT QA; however, they did not consider predicting the individual MLC leaf positions *priori* then predicting the gamma passing rate.

Even though several studies[8,15,16,27–35] were conducted on the MLC leaf positional errors for dynamic IMRT delivery through the analysis of the machine log file data[15,16,27–29] or electronic portal imaging device,[27,30–33] they may be considered passive and do not provide predictions ahead of time. ML methods can provide the active prediction of the MLC positional errors during the IMRT/VMAT delivery. Only one study[18] used conventional ML models for VMAT delivery using log file data of multiple institutions. Carlson et al.[18] investigated conventional ML algorithms (e.g. linear regression, random forest, and cubist) for predicting the MLC individual leaf positional errors. In this study, we explore other ML algorithms such as ANN models. Recently, ML-based neural network methods have notably been shown to outperform conventional ML algorithms for many applications.[36,37] In this study, we propose a state-of-the-art ANN method for predicting the MLC leaf positional deviations during the dynamic IMRT treatment delivery *priori* using log files data from a single institution.

2. MATERIALS AND METHODS

2.A. Patient data

A set of IMRT treatment plans of ten patients (different sites: head and neck, thorax, abdomen, and pelvis) was retrospectively retrieved randomly from a single-institution database. The plans were created on Eclipse TPS version 13.6 (Varian Medical Systems, Palo Alto, CA) with the progressive resolution optimizer (PRO) for fluence optimization and analytical anisotropy algorithm (AAA) for dose calculations. All plans were redelivered with sliding window mode on a Varian 2300 C/D Linac equipped with a Varian Millennium 120 HD MLC system (Varian Medical Systems, Palo Alto, CA). The MLC system consists of two banks of 60 leaf pairs, with 20 outer- and 40 inner-leaf pairs having widths of 1 and 0.5 cm, respectively. During the sliding window IMRT delivery, leaves are moving in one direction, while the beam is on.[1] The generated log files during the delivery were acquired for this study. After delivering each field, a pair of ASCII files (for carriages A and B) were created, resulting in a total of 200 files for all ten patients. Patient-specific IMRT plan verification program was in place for every patient before starting the treatment. The involved institution in this study follows the TG-142[3] protocol for Linac and MLC QA.

The Varian MLC dynamic log "dynalog" files[38] hold mechanical information (e.g. gantry, collimator, jaws, and leaves) and beam parameters (e.g. dose rate fraction, beam on/off states) data of the Linac throughout the treatment delivery sampled at 0.050 s time intervals. The complete log files contain the data of delivered parameters by the Linac and the planned parameters that are exported from the TPS to Linac. Both data, delivered and planned, are already synchronized. A comprehensive description of the files can be found at the Dynalog File Viewer reference guide.[38] The data were divided randomly into three subsets for training, validation, and testing the ANN model. A subset consisting of 70% of the data was used for training the developed architecture, 15% for validating and tuning, and 15% for testing and evaluating the validated model.

2.B. Features and parameters extraction

Parameters determined to be used as inputs to the ANN model for predicting the leaf positional deviations during the IMRT delivery *priori* are discussed here. The parameters were extracted or derived from the log file data. Despite the concern about the accuracy of the reported information in the log files, some studies have shown that the reported MLC positions are accurate.[32,39,40] Fourteen parameters were considered as inputs to the ANN model in this study as listed in Table I. Delivered leaf positional data were used as a target response for training the supervised ANN model. The effect of each of the chosen input parameters on the leaf positional errors based on what was reported in the literature is provided below:

2.B.1. Leaf positional errors vs dose fraction

The dose fraction that was recorded in the log files is measured by the Linac's monitor chamber. Noting that log file does not record the absolute dose or MUs; however, it stores accumulated dose fractions scaled between 0 (0% MU) and 25000 (100% MU) during each radiation field delivery. Hence, leaf positions for dynamic IMRT must be closely synchronized with MU delivery to avoid errors in dose delivered to the patient. Popple et al.[41] showed that when the planned trajectory (leaf position vs MU) requires velocities beyond the capability of the MLCs, the leaves fall behind the planned positions causing the MLC controller to momentarily hold the beam and thereby introduce dosimetric errors. Analysis of a study by Stell et al.[28] also indicated that up to 23% of the planned MUs at a dose rate of 600 MU/min was delivered during leaf motion exceeded the positioning tolerance (1 mm) during step-and-shoot IMRT delivery. The recorded dose fraction in the log file will affect the MLC speed and thus leaf position error.[42]

2.B.2. Leaf positional errors vs leaf motion status

Whether the leaf is starting, resting or accelerating at control points (as shown in Table I) may affect its positional accuracy. A study by Carlson et al.[18] showed that the model performance accuracy in predicting delivered MLC positions varies for moving leaves and leaves at rest. Higher accuracy was associated with leaves at rest compared to moving leaves. Park et al.[43] demonstrated that leaf acceleration does affect the leaf positional accuracy during VMAT delivery. In this study, the leaf is considered at rest if its previous and current calculated speeds are zero (Table I). Consequently, the leaf is determined to be starting movement if its previous speed was zero, and its current speed is higher than the previous one. The leaf is defined to be accelerating if its previous speed was not zero, and its current speed is higher than the previous one.

2.B.3. Leaf positional errors vs segment number

The segment number that is recorded in the log file represents the number of the segment that is currently executed. Errors in leaf positioning could be expected due to an increasing number of field segments because a larger number of segments would be clinically connected with a larger number of small MUs field shapes. Stell *et al.*[28] reported a correlation between the leaf error and the number of segments in an analysis study on step-and-shoot IMRT delivery data. However, Kerns et al.[15] showed no effect of this parameter on the leaf positional error for both step-and-shoot and dynamic IMRT deliveries. Therefore, we considered the parameter as an input for our model since the reported effects were contradicting.

2.B.4. Leaf positional errors vs beam ON/OFF states

The beam on/off flags in the log file indicate when and how often the radiation beam-on or beam-off status is

TABLE I. Parameters derived at control points to predict the multileaf collimator leaf positional deviations from the treatment planning system planning data transferred to the log files. The last column provides references that reported the effect of individual input parameter on leaf movement deviations or dose errors.

No.	Predictive parameters	Formula	Units	References
1	Leaf current field position (a)	–	100th of a mm	–
2	Leaf previous field position (b)	–	100th of a mm	–
3	Leaf next field position (c)	–	100th of a mm	–
4	Dose fraction	–	MU	[28,41,41]
5	Segment number	–	–	[15,28]
6	Beam ON flag/state	–	–	[15]
7	Beam hold-OFF flag/state	–	–	[15]
8	Gantry angle	–	10th of a degree	[31,49]
9	Carriage position	–	100th of a mm	[7,50]
10	Leaf gap	$abs(a(bankA) - a(bankB))$	100th of a mm	[7,30,35]
11	Leaf speed $\left(v(t)_{ab}\right)$	$abs(a - b)/time(0.050s)$	mm/s	[7,29,31,43]
12	Leaf starting status	$v(t)_{bc} > 0$ & $v(t)_{ab} = 0$	–	[18]
13	Leaf resting status	$v(t)_{bc} = 0$ & $v(t)_{ab} = 0$	–	[18]
14	Leaf accelerating status	$v(t)_{bc} > v(t)_{ab}$ & $v(t)_{ab} > 0$	–	[18,43]

asserted during the radiation delivery. In contrast to step-and-shoot IMRT delivery, the beam is on while the leaves are moving during the radiation delivery of each field in dynamic IMRT. A study by Kerns et al.[15] has shown that beam-on or beam-off states have no link to the MLC leaf positional errors. Since we plan in the future to extend our model for predicting dose errors, we included the beam-on and beam-off data in our model input parameters.

2.B.5. Leaf positional errors vs gantry angle

Multileaf collimator bank/carriage positioning may be affected by gantry rotation due to the heavyweight of the MLC assembly mounted in the gantry, which may cause drifts in the carriage drive and its supporting assemblies.[44,45] Studies[29,34,46–48] based on Elekta and Siemens MLC systems reported leaf deviations due to gravity within 0.3 mm at different gantry angles. In contrast, for the Varian machine, Rowshanfarzad et al.[31] reported an average shift in the leaf carriages of about 0.7 mm associated with gantry angles. Therefore, Rowshanfarzad et al.[31] and Ju et al.[49] concluded that the sag in both the gantry and the MLC system affects the patient dose and must be added for clinical considerations and during MLC leaf positional error analysis.

2.B.6. Leaf positional errors vs carriage/bank position

The leaf carriage could have a delay in communications with the MLC controller resulting in errors in leaves' positions.[7,50] Errors may also occur during the MLC calibration[5,33,44,51] which is considered to be the main cause of systematic errors in leaf banks.[5]

2.B.7. Leaf positional errors vs leaf gap

In IMRT delivery, the width of the gap (the opening between a leaf pair) and its position directly affects the accuracy of the delivered dose and spatial dose distribution.[7] LoSasso et al.[7] reported that dose error correlates with leaf gap error and not necessarily with individual leaf position error. Therefore, correct MLC positioning is essential for highly modulated IMRT fields,[35] particularly for fields with small gaps.[30] The effect of leaf gap on the leaf positional errors may greatly vary between sliding widow IMRT and VMAT delivery due to the nature of leaf movement and direction. In sliding window IMRT, the opposing leaf banks move in the same direction. As a result, small leaf gap errors are expected during delivery. In this study, the leaf gap at any control point was calculated as the absolute difference between the leaf positions of an opposing leaf pair (Table I) and was included as an input parameter as it depends on the accuracy of the leaf position.

2.B.8. Leaf positional errors vs leaf speed

During the dynamic IMRT delivery, leaf speed is crucial because the leaves move, while the beam is on. Studies[7,29,31,43] have shown that the speed of the MLC leaf during IMRT dynamic delivery does affect the leaf positional errors. The higher leaf speeds are associated with larger MLC positional errors, which cause errors in the dose delivered to the patient. In this study, leaf speed at any control point was calculated as the absolute difference between its current position and the previous position divided by a sampling time interval of 0.050 s (Table I).

2.C. The ANN algorithm

Artificial neural networks[52] are models inspired by biological neural networks and are used to approximate functions. In ANN, several layers of neurons are setup. Each "neuron" has a weight that determines its importance. Each layer receives data from the previous layer, calculates a score and passes the output to the next layer. While ANNs commonly feature one or two hidden layers and are considered as supervised ML, deep learning algorithms have a higher number of hidden layers. In an ANN architecture, two or more of the neurons can be combined in a single layer and a particular network could contain one or more such layers. ANNs have the advantage of working even if one or a few units fail to respond to the network. However, ANNs are referred to as "black box" models that provide very little insight and require large training data sets.[53]

As shown in the architecture of Fig. 1, an ANN of one hidden layer with 20 neurons was developed to map 14 input neurons (parameters shown in Table I) to one output neuron for each MLC leaf. A total of 120 ANN architectures were developed, with every architecture representing an individual leaf. A feed-forward ANN was used in building the architecture with the tan-sigmoid transfer function in the hidden layer and linear transfer function in the output layer. The learning model architecture was designed to use the derived parameters as inputs and the leaf delivered positions data as target response. To train the ANN architecture, we used the backpropagation algorithm that updates weight and bias values according to Levenberg-Marquardt optimization.[54,55] The transfer function (neuron model) and backpropagation optimization algorithm chosen in this study were part of the default settings for the feed-forward network in the MATLAB Neural Net Fitting application (MathWorks, Natick, MA, USA). We tried other available backpropagation optimization algorithms such as Bayesian regularization and scaled conjugate gradient algorithms. However, the best results were

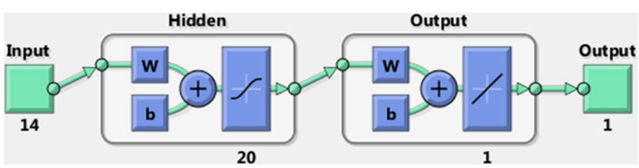

FIG. 1. A neural network architecture for one leaf to predict the multileaf collimator leaf positional deviations during the intensity modulation radiotherapy treatment delivery *priori*. [Color figure can be viewed at wileyonlinelibrary.com]

obtained with the Levenberg-Marquardt training method. The optimal number of hidden neurons (20) as shown in Fig. 1 was determined by changing the number of neurons and evaluating the performance taking into account the computation time. The training data set is composed of 70% of the total data used in the study. The trained model was cross-validated and tested for its accurate prediction on new unseen data (30% of total data). During the cross-validation and tuning process, the probability of the model-overfitting problem was minimized and its generalizability improved. The MATLAB 2016b software with implemented Statistics and ML Toolbox was used for developing the ANN model.

2.D. The proposed model

The proposed model flowchart for the prediction of individual leaf positional deviations is shown in Fig. 2. We implemented an ANN model to predict the leaf positional deviations during the delivery *priori* from the planned ones, using the log files data.

The proposed method is composed of the following steps. First, the information recorded in the log files by a Varian Linac is acquired. Second, important parameters are extracted and fed into the ML predictive model as input parameters (Table I). Third, an ANN feed-forward architecture is trained and then tuned using the input parameters and delivered leaf positions as target response output (Fig. 1) for all 120 MLC leaves. Finally, the validated model is used for predicting the individual leaf positional deviations during the treatment delivery *priori*.

2.E. Evaluation

The mean squared error (MSE) metric was used to evaluate the performance of the trained ANN model and to verify its prediction accuracy. The performance measure indicates how well the trained model will perform on the unseen data. Another metric employed to check the model performance was the linear regression analysis of the predicted and delivered leaf positional errors. The error histogram metric was also utilized to show the distribution of the leaf positional errors.

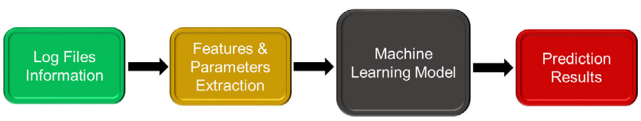

FIG. 2. The proposed method workflow for predicting the leaf positional deviations. [Color figure can be viewed at wileyonlinelibrary.com]

3. RESULTS

3.A. MLC leaf deviations

The differences between the planned and delivered MLC leaf positions are shown in Fig. 3 for one patient (only one field). The MLC leaf deviation (error) is defined and calculated as the difference between the planned and delivered individual leaf positions. The positional errors reflect the performance of each MLC leaf during the dynamic IMRT treatment delivery.

The maximum discrepancy between the planned and delivered leaf position error is about 1.2 mm as shown in Fig 3, in this case. Dosimetrically, this deviation (1.2 mm) in the leaf positioning could result in about 6% dose error in the PTV during the dynamic IMRT delivery.[9–11] We noticed that the values of delivered leaf positions are less (minus sign) than the planned positions, in this case. It could be interpreted as a systematic shift in one motion direction. It should be pointed here that leaf motion direction was not taken into account in this study, because in sliding window IMRT delivery the leaf motion is always in one direction. This simple leaf deviation display can be used for evaluating the performance of the MLC system and would allow the identification of any specific leaf that needs repair and/or calibration. Also, it can be used to give early warning for MLC movement problems that can result in clinical downtime, similar to the approach proposed by Agnew et al.[27]

3.B. ANN prediction results

The prediction results of the proposed ANN-based model for MLC leaf positional deviations during the

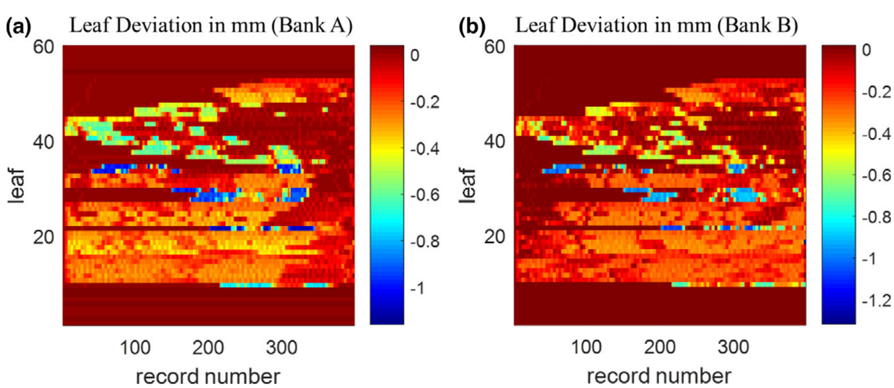

FIG. 3. A maximum leaf deviation for bank (a) (left) and (b) (right) for one patient (only one field). Leaf deviation = delivered position — planned position. Record number in the x-axis represents the data recorded for each leaf every 0.050 s time interval during the whole treatment period. [Color figure can be viewed at wileyonlinelibrary.com]

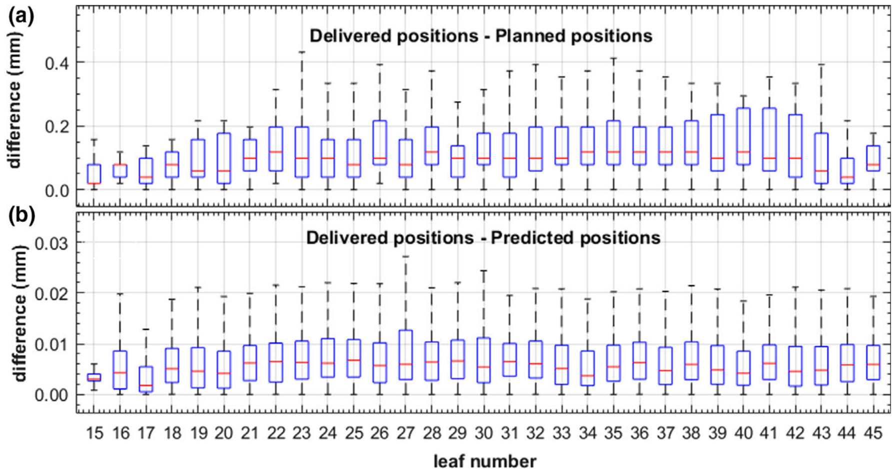

FIG. 4. Multileaf collimator leaves positional deviations (difference in mm) of the treatment planning system planned (a) and the model predicted (b) positions from the delivered positions. Only leaves of one bank that are set in motion during the treatment were included in this plot. [Color figure can be viewed at wileyonlinelibrary.com]

dynamic IMRT delivery *priori* are shown in Fig. 4 (for one patient). The predicted leaf positions were in a very good agreement with the delivered positions. The results were expressed with a boxplot displaying the differences in mm for each leaf.

Each box in the boxplot represents the positional deviations for an individual leaf. The line in the middle of each box is the sample median. The median is not always in the center of the box. The median shows the sample obliquity (skewness) of the sample distribution. The top and bottom lines of each box are the 25th and 75th percentiles of the data samples, respectively. The distances between the top and bottom lines are the interquartile ranges. The two vertical lines extending above and below each box are the whiskers. Whiskers extend from the ends of the interquartile ranges to the furthest data point. Leaves shown in the graph are the moving ones for this example, the parked leaves were excluded. The input parameters included in this study were found to be predictive. Our predicted individual leaf positions closely matched the delivered positions with a maximum difference of about 0.026 mm.

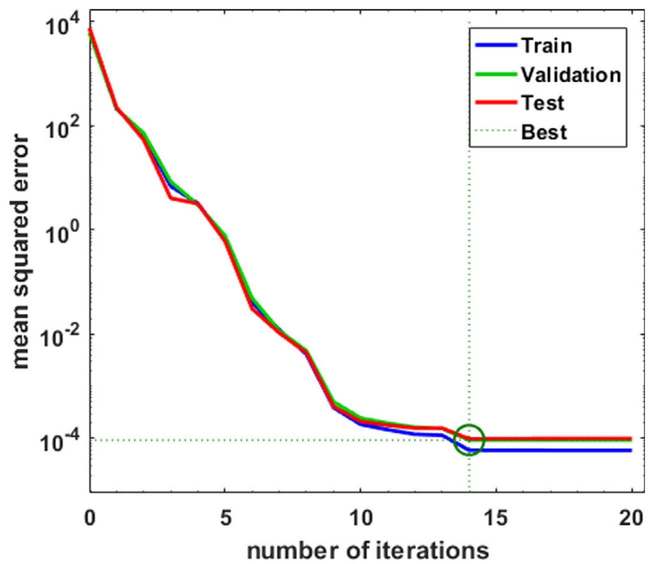

FIG. 5. The artificial neural network model performance evaluated using the mean squared error (MSE) for the prediction of one leaf positional deviations during training, validation, and testing. The lowest MSE was 0.0001 mm^2 achieved at iteration # 14. [Color figure can be viewed at wileyonlinelibrary.com]

3.C. Evaluation results

The ANN model performance was evaluated using the MSE as shown in Fig. 5 for one leaf. The MSE rapidly decreased as the ANN model was further trained. An MSE of 0.0001 mm^2 (root MSE = 0.0097 mm) after several iterations ($n = 14$) was achieved.

Figure 5 shows the number of iterations needed for the model to achieve the best possible validation performance (bias vs variance tradeoff) during the model optimization. Generally, the error decreases after a few iterations of training but might start to increase on the validation data set as the network starts overfitting the training data. Beyond the 14th iteration, the MSE falls to below 0.0001 mm^2 (root MSE = 0.0097 mm) and no significant reduction is achieved after that. The validation and test curves are very similar with no overfitting observed during the training. The very small value of RMSE obtained for our model characterizes the very high accuracy of the model performance.

The histogram of errors is also another metric for evaluating our model performance as illustrated in Fig. 6 for one leaf. The histogram plot in Fig. 6 shows how the error sizes are distributed. Typically most errors are near zero, with very few errors far from that.

The data follows a Gaussian distribution with a peak at the mean value around zero. The testing and validating errors were less than the training errors as expected.

The regression plots, displaying our model outputs plotted in terms of the associated target values, are shown in Fig. 7 for one leaf. The correlation coefficient, R, was perfect

(R = 0.999) in all plots indicating an excellent agreement between the predicted and delivered leaf positions for the training, validation, and testing data.

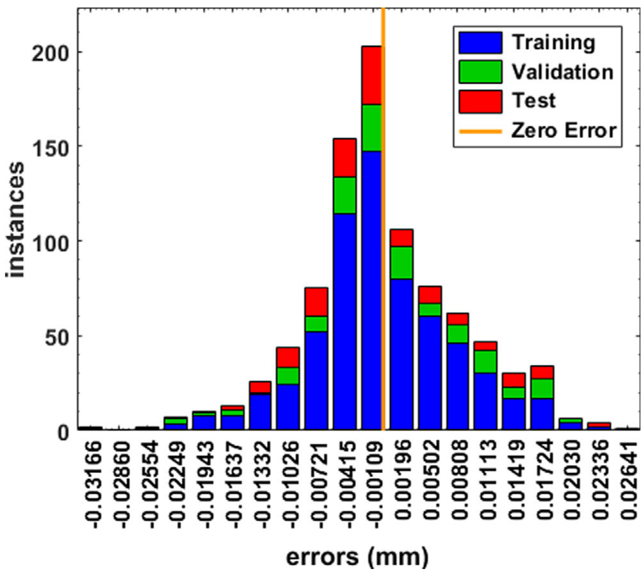

FIG. 6. The histogram plot of error values for one leaf during training, validating, and testing of the artificial neural network model. [Color figure can be viewed at wileyonlinelibrary.com]

The dashed line in the plot (Fig. 7) represents the perfect results when the predicted leaf positions are equal to the delivered ones. The solid line represents the best-fit linear regression line between predicted and delivered leaf positions.

4. DISCUSSION

Differences between planned and delivered leaf positions are a crucial source of error in dose distribution during dynamic radiotherapy treatment delivery such as dynamic IMRT and VMAT. In this study, we developed a state-of-the-art ML-based ANN method (Fig. 2) for accurately predicting individual MLC leaf positional deviations during the dynamic IMRT treatment delivery *priori* using log file data from a single institution. It has been reported in the literature[9–11] that there is a correlation between the MLC positional deviations and the errors in dose delivered to the patient during dynamic IMRT delivery. An average position error of 0.2 mm (or 1 mm) can cause 1% (or 5%) dose error in the PTV. Another study by Nithiyanantham et al.[56] showed that MLC positional errors beyond ±0.3 mm can have a significant influence on the IMRT dose distributions. Therefore, Budgell et al.[35] recommended that accurate dose delivery for IMRT fields requires better than 1 mm (AAPM TG-142 report[3] tolerance) accuracy in leaf positioning.

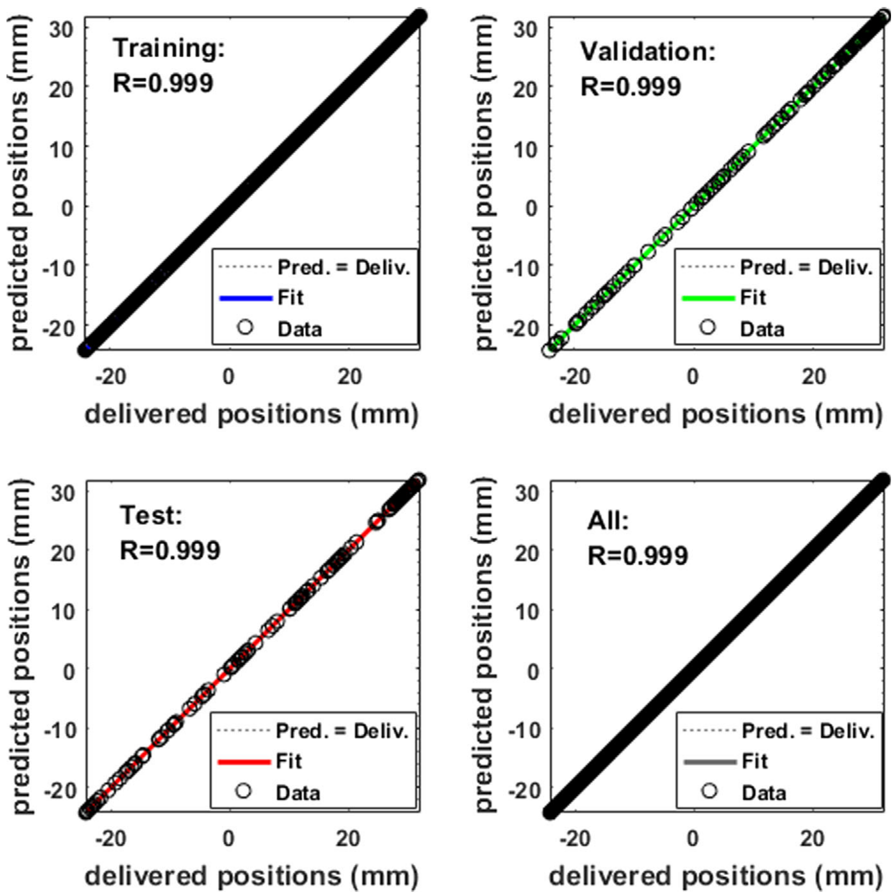

FIG. 7. The regression plots of the model performance for the training, validation, testing data, and all combined for one leaf. The plots show the relationship between the predicted and delivered leaf positions. [Color figure can be viewed at wileyonlinelibrary.com]

Parameters thought to have predictive ability for the leaf positional deviations were extracted and calculated from the log files data (Table I) and used as inputs to the ANN model. Although we did not practically examine the individual correlation of these parameters (Table I) with the target response output (delivered leaf positions) in this study, their effects on the leaf positional deviation and dose distribution errors have been reported in the literature (TableI). Most of the chosen parameters such as leaf velocity[7,30,43] leaf motion status,[18,43] leaf gap,[7,30] dose fraction,[28,41,42] segment number,[28,42] carriage position,[31,49] and gantry angle[31,49] were found to be correlated with leaf positional errors. The correlation between the parameters with leaf positional errors vary from weak to strong. However, two parameters beam on/off states were not reported to be predictive of leaf positional errors.[15] Inclusion of parameters that have insignificant or weak effects could lead to over-fitting of the training data. However, this was not observed in our model performance. Jaws' positions[7,34,57] were reported to be predictive but the authors did not consider these parameters in this study because the X- and Y-jaws of the Varian 2300 C/D Linac are fixed during IMRT delivery. However, we recommend including the jaws' positions as input parameters for the ANN framework for Linacs that support jaw-tracking delivery (Varian TrueBeam series). Our model successfully predicted the leaf positional errors when evaluated on the testing data set as shown in Fig. 5. The leaf motion direction was not taken into account in this study because leaves on opposing banks all move in the same direction. By referring to the published model-based[18] and statistical analysis[15,16] studies, leaf speed has been found to have an approximately linear correlation with error in MLC leaf positions and is the most predictive parameter among the tested ones.

To build the model, data were randomly distributed to the following scheme: 70% for training, 15% for validating and tuning, and 15% for testing the final model. Technically, this distribution with other alternative ones (e.g. 60%, 20%, and 20%, respectively) was found to be optimal and commonly used in building and validating a successful ML model. It provides a good compromise for the bias (overfitting — good training results and poor testing results for data example not seen in the training) vs variance or regularization (underfitting — poor training results and good testing results for data not seen in the training) tradeoff. A feed-forward ANN architecture was built to map the input parameters with the output to predict the MLC leaf positional deviations during the dynamic IMRT delivery *priori*. The number of neurons (20) in the hidden-layer was iteratively determined (Fig. 1). The tan-sigmoid transfer function and the Levenberg-Marquardt optimization algorithms part of the default settings for the feed-forward network in the MATLAB Neural Net Fitting application have given the best results. Neural network models suffer from interpretability issue[53] ("black box" stigma) by providing very little insight and need massive data for training to avoid overfitting problems. In contrast, ML-based NN algorithms (ANN, CNN, and deep learning NN) are associated with high predictive accuracy and commonly outperformed other ML model in many applications.[36,37]

The ANN model accuracy was assessed with MSE having a value of 0.0001 mm^2 (RMSE = 0.0097 mm) as shown in Fig. 5 for individual MLC leaf position. The high accuracy of our ANN model outperforms the reported accuracies by Carlson et al.[18] for cubist (0.196 mm RMSE), linear regression (0.193 mm RMSE), and random forest (0.200 mm RMSE) models on VMAT data. The maximum mean absolute error (MAE) value over all leaves showed that the ANN model in this study achieved the lowest value (0.006 mm) when compared to those reported by Carlson et al.[18] for cubist (0.075), linear regression (0.086 mm), and random forest (0.089 mm) models. A perfect fit between the predicted and delivered leaf positions (R = 0.999) was also observed (Fig. 7) during the model training, validation, and testing. TPSs do not account for leaf positional error. Therefore, the prediction results of this study could be integrated into TPS for the actual application in the dose calculation and optimization, and/or virtual patient-specific IMRT QA.

A few limitations associated with this study could be highlighted. *First*, log files recorded data do not include information such as the TPS version, Linac model, MLC system, and other important clinical parameters. These parameters could not be the same for different institutions and lead to discrepancies in predictions. Hence, it is important to retrain the proposed ANN model on the machine's given data (machine-specific and leaf-specific model) before using it for prediction. *Second*, the computation time for training and validating the ANN model in our data set was approximately 20 min for one MLC on Intel (R) Core (TM) 8.00 GB RAM, CPU @ 2.50 GHz processor with 64-bit Operating System. Given that not all MLCs will be in motion during every treatment delivery, the total time for training and validating the 120 MLC leaves were roughly a few hours (~5 h) with parallel computing. When the model was used for a prediction it took less than a minute to provide the results. *At last*, the data used in this study were collected from a single-institution database and only one MLC system type (Varian Millennium 120 HD MLCs system) was considered.

5. CONCLUSIONS

In this study, we proposed an ML-based ANN method for predicting the individual MLC leaf positional deviations during the dynamic IMRT treatment delivery *priori*. We implemented a feed-forward ANN with the sigmoid transfer function in a hidden-layer and linear transfer function in the output layer to develop a prediction model for the MLC leaf positional deviations. The model successfully predicted the individual MLC leaf positional deviations with high accuracy. Our model outperformed the reported accuracy in the literature of various ML models for predictions of the MLC leaf positional deviations. The results of this study could be extended to actual application in the dose calculation/optimization, hence enhancing the gamma passing rate for patient-specific IMRT QA.

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CONFLICT OF INTEREST

The authors have no relevant conflict of interest to disclose.

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