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Enhancing Linear Accelerator Performance through Predictive Modeling of Downtime and Interlock Incidents

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ABSTRACT

Background and Purpose: Radiation therapy is a critical modality in cancer treatment, relying on medical Linear Accelerators (LINACs) to deliver precise radiation doses while minimizing exposure to surrounding healthy tissues. LINAC systems generate extensive operational and administrative data that are managed by integrated control software. Safety interlocks are designed to automatically interrupt treatment when operational parameters exceed predefined thresholds. Component failures and interlock events can lead to unplanned machine downtime, disrupting clinical workflows, delaying patient treatments, and increasing operational costs. This study aims to develop predictive machine learning models for LINAC interlock occurrences and downtime events to enhance system reliability and reduce service interruptions.

Materials and Methods: Operational data were collected from the machine malfunction logbook of a Varian Clinical System at Square Hospitals Ltd. Two datasets were constructed: one for predicting interlock events and another for forecasting downtime duration. An LSTM (Long Short-Term Memory) neural network was implemented for interlock prediction and trained over 300 epochs. For downtime prediction, six machine learning models were developed and evaluated. Model performance was assessed using accuracy metrics and mean squared error (MSE), with k-fold cross-validation applied for model validation.

Results: The LSTM model achieved an accuracy of **72%** in predicting interlock events, with a **top-2 prediction accuracy of 84%**. Among the evaluated downtime prediction models, **Bayesian Regression** demonstrated the best performance, achieving an accuracy of **98.21%** and a **Mean Squared Error (MSE) of 0.0179**. Cross-validation results confirmed the robustness and consistency of the predictive models.

Conclusion: Machine learning can significantly enhance the prediction and analysis of LINAC interlock and downtime events, enabling proactive maintenance strategies. These findings support improved patient care, workflow efficiency, and hospital management by minimizing service disruptions in radiation therapy.

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Introduction

LINAC downtime directly delays cancer treatment — critical in low- and middle-income countries (LMICs), where access is already limited (some countries have only 1 unit for 20M+ people). Components contributing ~80% of LINAC costs are kV system, MV system, Thyratron, ion chamber, MLC, PCB and annual LINAC maintenance costs could range $3,000–$91,740 USD (median $41,390).Failures cluster in collimation and acceleration subsystems, correlating with usage rather than environmental factors. LINACs in low- and middle-income countries show significantly higher downtime due to less stable designs of the facility.

Our purpose is to Build machine learning models to predict (1) interlock events and (2) downtime duration for a Varian Clinac LINAC, to support predictive maintenance and reduce treatment interruptions.

Methods and Materials

Data source: Varian Clinac malfunction datalog, Department of Radiation Oncology, Square Cancer Centre / Square Hospitals Ltd. — includes malfunction/recovery date-time, total downtime, interlock codes, service time, distance, and other parameters.

Tools: Python (VS Code); Pandas, NumPy, Seaborn, Matplotlib, TensorFlow, Keras, scikit-learn.

Interlock Prediction: Long Short-Term Memory Model or LSTM Model (deep learning / sequence model)

Downtime Prediction — 6 regression models compared: Support Vector Regression (SVR), Random Forest Regression, Decision Tree, ElasticNet Regression, LASSO Regression & Bayesian Regression.

Evaluation: Evaluated via k-fold cross-validation,

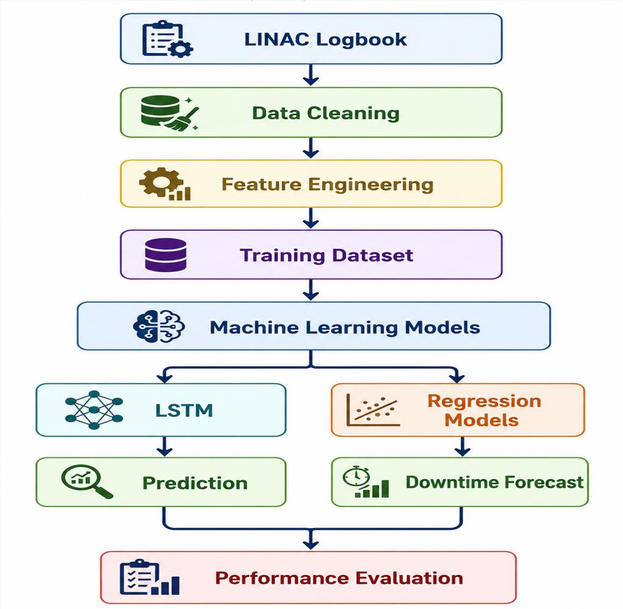


Figure 1: Process flowchart for machine learning analysis

Chart 01. Flow Chart for interlock prediction model.

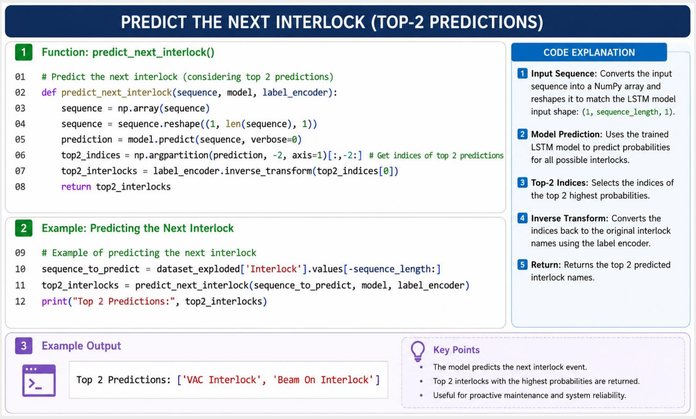


Figure 02. Coding visualization for LSTM model building.

Chart 02. Flow Chart for interlock prediction model.

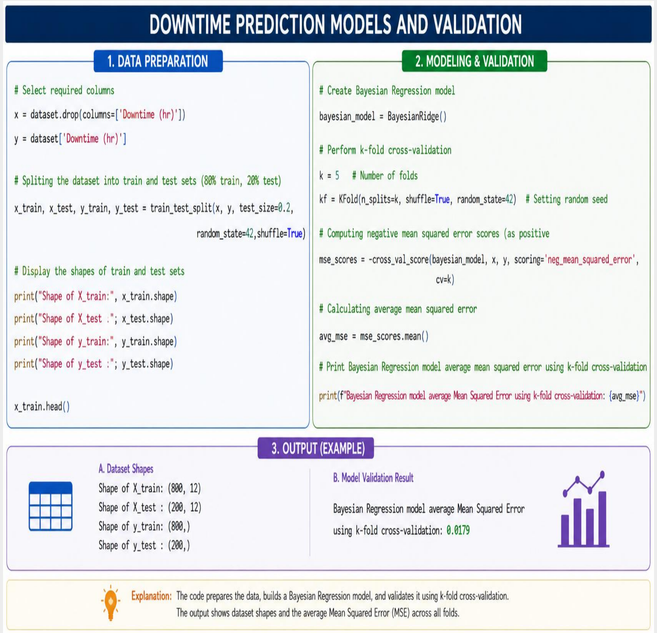


Figure 03: Machine learning downtime prediction guide

Results

Interlock Prediction (LSTM): Test Accuracy: **72%,** Top-2 Accuracy: **84%** , Bayesian Regression Accuracy: **98.21%** , MSE: **0.0179**

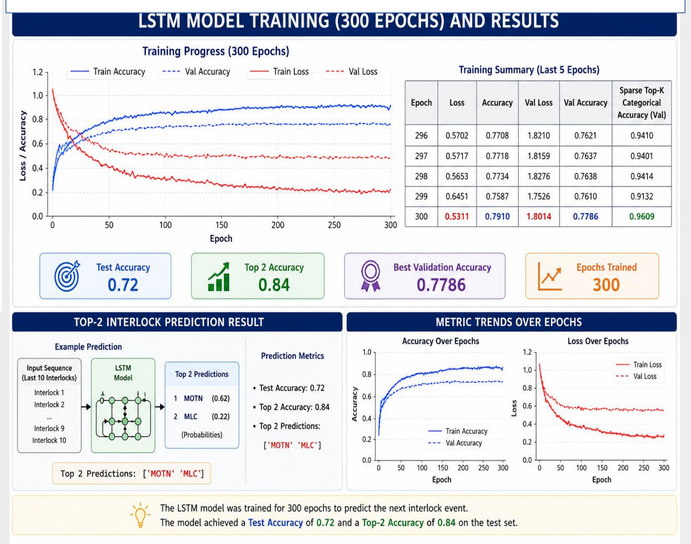
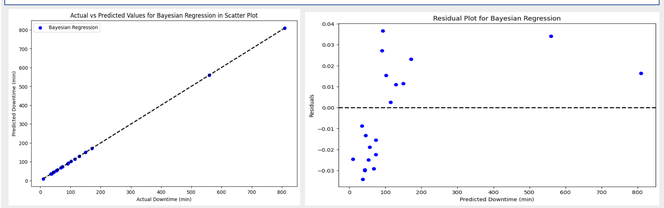


Figure04: LSTM training and prediction results

Downtime Prediction: Bayesian Regression achieved average Mean Squared Error of 0.0179 across k folds ≈ 1.79% prediction error.



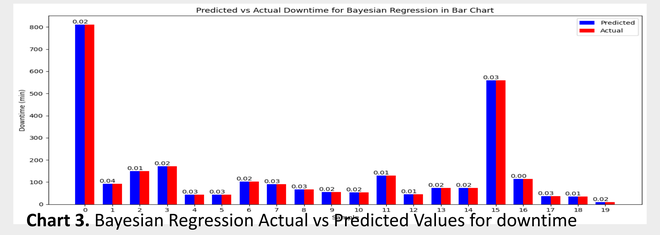


Chart 3. Bayesian Regression Actual vs Predicted Values for downtime

Model	Accuracy / Performance
Bayesian Regression	98.21% accuracy, MSE = 0.0179 (best)
ElasticNet Regression	Strong accuracy & consistency
LASSO Regression	Strong accuracy & consistency
Support Vector Regression	Underprediction issues
Random Forest	Underprediction in specific cases
Decision Tree	Underprediction in specific cases

Table 1. Downtime Prediction & model comparison (by MSE, k-fold CV):

Discussion

The LSTM model effectively captured sequential patterns in LINAC interlock events, achieving **72% test accuracy** and **84% top-2 prediction accuracy**, demonstrating its potential for anticipating future machine faults. Among the evaluated regression models, **Bayesian Regression** provided the most accurate and robust downtime prediction, while **ElasticNet** and **LASSO** also showed strong predictive performance and consistency. In contrast, **Support Vector Regression (SVR)**, **Random Forest**, and **Decision Tree** models exhibited reduced accuracy, primarily due to underprediction in selected cases. These findings suggest that combining deep learning with regression-based predictive modeling can support proactive LINAC maintenance, reduce unexpected downtime, and improve radiotherapy workflow efficiency and treatment continuity.

Conclusions

ML models successfully predicted interlock and downtime events for a Varian Clinac LINAC. LSTM was effective for interlock event prediction. Bayesian Regression was the most reliable downtime predictor (98.21% accuracy). These models offer a framework for predictive maintenance — supporting operational efficiency and more timely, uninterrupted patient care.

Machine learning enables predictive maintenance, reduces LINAC downtime, and improves radiotherapy workflow.

References

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