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Evaluating the Radiology Exam Turnaround Time Using the RIS Workflow Logs: An AI-Based Predictive Modeling Approach

Joseph A. Jose, RRT[1], Dr. Erwin M. Faller[2]
St. Bernadette of Lourdes College[1] , Philippines Holy Child Central College Inc.[2]
https://orcid.or//0009-0005-1531-6336[1]: https://orcid.or//0000-0001-8269-7304[2].
jjose@sblc.edu.ph[1] , erwinfaller@hcci.edu.ph[2]

ABSTRACT

This study developed and evaluated machine learning models to predict radiology examination turnaround time (TAT) using Radiology Information System (RIS) workflow logs while identifying operational factors associated with prolonged turnaround time. A retrospective quantitative design was employed using 21,870 de-identified radiology examination records obtained from a Level III private hospital. Three machine learning algorithms—Linear Regression, Random Forest, and XGBoost—were developed and evaluated using a 70:30 training-testing split with five-fold cross-validation. Among the models, Random Forest achieved the lowest Mean Absolute Error (154.30 minutes), whereas XGBoost demonstrated the highest explanatory power (R^2 = 0.59). The most influential predictors of TAT were the day of the week, request hour, daily examination volume, time of day, and hourly examination volume. Workflow analysis further identified the interval between resident interpretation and report transmission as the primary operational bottleneck contributing to delays. Although the study was limited to a single institution and relied on retrospective RIS data without incorporating variables such as radiologist experience or equipment downtime, the findings demonstrate the potential of predictive analytics to support staffing optimization, workload forecasting, scheduling, and workflow improvement. Overall, this study provides local evidence supporting the application of artificial intelligence (AI) to enhance radiology workflow management and operational efficiency in Philippine hospitals.

Keywords: Artificial Intelligence; Machine Learning; Radiology Information System; Turnaround Time; Random Forest; XGBoost; Predictive Analytics.

INTRODUCTION

Radiology examination TAT is an important indicator of departmental efficiency because delayed reports can affect diagnosis, treatment, patient satisfaction, and hospital operations (American College of Radiology, 2023). RIS routinely captures workflow data that can be used to evaluate operational performance, yet these data are often underutilized for predictive management. Recent advances in machine learning provide opportunities to model complex workflow patterns and improve operational decision-making (Rajkomar et al., 2019). However, evidence on AI-assisted radiology workflow optimization remains limited in Philippine healthcare settings. To the authors' knowledge, this is among the first studies in the Philippines to apply machine learning to predict radiology examination turnaround time using routinely collected RIS workflow logs.

Statement of the Problem

This study aimed to develop and evaluate machine learning models for predicting radiology examination TAT using historical RIS workflow data. Specifically, it sought to identify operational factors associated with prolonged turnaround time, compare the performance of Linear Regression, Random Forest, and XGBoost, determine the primary workflow bottleneck, and provide recommendations for improving radiology department efficiency.

Scope and Delimitations

The study analyzed retrospective RIS workflow data from a single Level III private tertiary hospital in Quezon City. The study included only routinely collected operational variables and excluded factors such as radiologist experience, equipment downtime, staffing ratios, and patient acuity.

Review of Related Literature

Previous studies have identified examination volume, reporting workload, staffing, and temporal factors as major determinants of radiology turnaround time (Hall, 2013; Kallmes et al., 2015; Rathnayake et al., 2017). Radiology Information Systems provide operational data suitable for workflow analysis, while machine learning algorithms such as Random Forest and XGBoost have demonstrated superior performance for complex healthcare datasets (Breiman, 2001; Chen & Guestrin, 2016). Despite these advances, studies applying machine learning to radiology workflow optimization in the Philippine setting remain limited.

Theoretical Framework

The study was guided by Queuing Theory, which explains delays resulting from increasing service demand, and the Theory of Constraints, which identifies workflow bottlenecks that limit overall system performance.

Conceptual Framework

The framework assumes that operational variables extracted from the RIS (inputs) are processed using machine learning algorithms (process) to predict radiology turnaround time and identify workflow bottlenecks (outputs).

Research Design

The study employed a retrospective quantitative research design using historical RIS workflow data to develop and evaluate machine learning prediction models.

Research Steps

The workflow consisted of data extraction, data cleaning, feature engineering, model development, model evaluation, and workflow bottleneck analysis**.**

Data Collection and Sample Selection

We extracted 25,350 radiology examination records, of which 21,870 met the inclusion criteria after preprocessing and data cleaning.

Data Analysis Methods

Linear Regression, Random Forest, and XGBoost models were evaluated using five-fold cross-validation. Model performance was assessed using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2).

Research Hypotheses and Validation

H_0: There is no difference in the predictive performance of Linear Regression, Random Forest, and XGBoost models for predicting radiology examination turnaround time.
H_1: There is a difference in the predictive performance of Linear Regression, Random Forest, and XGBoost models for predicting radiology examination turnaround time.
Model validation was performed using a 70:30 training-testing split, five-fold cross-validation, and hyperparameter optimization through GridSearchCV. Prediction accuracy was evaluated using MAE, RMSE, and R^2 to ensure model robustness and minimize overfitting.

Study Limitation and Ethical Considerations

The study was conducted in a single tertiary private hospital using retrospective operational data, which may limit the generalizability of the predictive models to other healthcare settings. The Ethics Review Board of St. Bernadette of Lourdes College granted ethical approval, and institutional permission was secured before data extraction. The study utilized de-identified retrospective data in accordance with the Philippine Data Privacy Act of 2012 (Republic Act No. 10173).

RESULTS

We extracted 25,350 radiology examination records from the RIS. After removing duplicate records, incomplete timestamps, canceled examinations, inconsistent workflow sequences, and implausible turnaround times, 21,870 complete records were retained for analysis. This cleaned dataset served as the basis for all descriptive and predictive analyses.
Radiology turnaround time demonstrated a right-skewed distribution, indicating that most examinations were completed within a consistent timeframe, while a small proportion experienced prolonged delays. The 90th and 95th percentile turnaround times were 1,435 and 1,669 minutes, respectively, reflecting occasional workflow inefficiencies.

SOP 1: To identify the relevant data features from the hospital's RIS workflow logs that can be used to predict radiology examination turnaround time.

Feature relevance analysis identified request hour, daily examination volume, time of day, hourly examination volume, and day of the week as the strongest predictors of turnaround time after excluding the resident interpretation-to-report transmission interval to prevent target leakage. These findings indicate that temporal and workload-related factors contributed more substantially to turnaround time than patient-related variables.
Temporal analysis showed that Monday had the longest median turnaround time (1,183 minutes), whereas Tuesday (760 minutes) and Thursday (705 minutes) had the shortest. Turnaround time was also longest during the afternoon (1,088 minutes) and during peak operating hours (1,051 vs. 853 minutes), indicating that increased workload contributed to reporting delays.

SOP 2: To evaluate which machine learning regression model provides the most accurate prediction of radiology examination turnaround time.

Among the evaluated machine learning models, Random Forest achieved the lowest Mean Absolute Error (MAE = 154.30 minutes), while XGBoost demonstrated the highest coefficient of determination ($R^2 = 0.59$) and the lowest Root Mean Squared Error (RMSE = 277.69 minutes). Linear Regression showed substantially poorer performance (MAE = 305.62 minutes; $R^2 = 0.14$). Owing to its superior prediction accuracy, Random Forest was selected as the final predictive model.

SOP 3: To analyze the operational workflow factors that significantly contribute to prolonged radiology examination turnaround time.

Permutation feature importance confirmed that day of the week, daily examination volume, request hour, time of day, and hourly examination volume were the most influential predictors. Workflow interval analysis further identified the period between resident interpretation and report transmission as the principal bottleneck, suggesting that improvements in report verification and transmission may have the greatest impact on reducing turnaround time.

SOP 4: To develop recommendations on how the predictive model can be used to optimize radiology workflow operations.

From a hospital administration perspective, the findings demonstrate that predictive analytics can transform routinely collected workflow data into actionable operational intelligence. Integrating machine learning models into existing RIS platforms may enable administrators to anticipate workflow congestion, optimize staffing allocation, improve scheduling, prioritize reporting tasks, and monitor departmental performance in real time. Such applications support evidence-based management by allowing proactive interventions before delays affect patient care. Rather than serving solely as documentation systems, RIS can become valuable tools for operational planning and continuous quality improvement.

DISCUSSION

The study identified day of the week, request hour, daily examination volume, time of day, and hourly examination volume as the strongest predictors of radiology examination turnaround time (TAT), indicating that workflow efficiency is driven primarily by temporal and workload-related factors rather than patient characteristics. Longer TATs on Mondays, during afternoon shifts, and during peak operating hours support Queuing Theory, which explains that waiting times increase as service demand approaches or exceeds available capacity. These findings suggest that workload-based staffing and scheduling may improve reporting efficiency and are consistent with previous studies identifying examination volume and staffing patterns as major determinants of radiology performance (Hall, 2013; Kallmes et al., 2015; Rathnayake et al., 2017).

The machine learning models demonstrated that routinely collected RIS workflow data can effectively predict radiology TAT. Random Forest achieved the lowest Mean Absolute Error (154.30 minutes), indicating the highest practical prediction accuracy, while XGBoost showed the greatest explanatory power ($R^2 = 0.59$). Both ensemble learning models outperformed Linear Regression, confirming that radiology workflow exhibits complex nonlinear relationships better captured by advanced machine learning techniques. These findings support the application of artificial intelligence as a decision-support tool for staffing, scheduling, and workflow optimization in radiology departments, while providing local evidence for Philippine hospitals.

Workflow interval analysis further identified the period between resident interpretation and report transmission as the primary operational bottleneck contributing to prolonged TAT. Consistent with the Theory of Constraints, this finding suggests that improving report verification, consultant review, communication, structured reporting, and electronic report transmission is likely to produce greater improvements in operational efficiency than expanding imaging capacity alone.

SUMMARY

Overall, this study demonstrates that machine learning provides an effective approach for predicting radiology examination turnaround time and identifying operational factors associated with workflow delays. By combining predictive modeling with workflow analysis, the study offers evidence-based strategies for improving staffing, scheduling, reporting processes, and resource allocation. These findings contribute to the growing body of evidence supporting AI as a practical tool for enhancing radiology department efficiency and strengthening hospital operational performance.

CONCLUSION

This study demonstrated that machine learning can effectively predict radiology examination turnaround time using routinely collected RIS workflow data. Among the evaluated models, Random Forest achieved the highest practical prediction accuracy, while XGBoost showed the greatest explanatory power. The findings also identified temporal and workload-related factors, particularly day of the week, request hour, and examination volume, as the strongest predictors of turnaround time. The study highlights the potential of predictive analytics to support evidence-based workflow management and improve the efficiency of radiology services.

RECOMMENDATIONS

Healthcare institutions should consider integrating machine learning models into existing RIS to support workload forecasting, staffing allocation, and scheduling decisions. Future studies should validate the proposed models using multicenter datasets and incorporate additional operational variables, such as radiologist experience, staffing ratios, examination complexity, and equipment downtime, to improve model generalizability and predictive performance.

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AI DECLARATION STATEMENT

AI -supported tools helped with grammar and structure in creating this article. No AI tools were used to collect, analyze, or interpret data; all authors are credited for their academic contributions.

REFERENCES

American College of Radiology. (2023). *ACR practice parameter for communication of diagnostic imaging findings*. American College of Radiology. https://www.acr.org

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794. https://doi.org/10.1145/2939672.2939785

Goldratt, E. M. (1990). *What is this thing called theory of constraints and how should it be implemented?* North River Press.

Gross, D., et al. (2018). *Fundamentals of queueing theory* (5th ed.). Wiley.

Hall, R. W. (2013). *Patient flow: Reducing delay in healthcare delivery* (2nd ed.). Springer.

Kallmes, D. F., et al. (2015). Operational efficiency in radiology. *Radiology Management, 37*(4), 34–41. https://doi.org/10.1016/j.acra.2015.05.007