Research Article

AI Based Predictive Modelling for Internal Quality Control: A Machine Learning Approach Using Altair RapidMiner

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Article Info

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Keywords

Internal Quality Control, Machine Learning, Predictive Analytics, Altair RapidMiner, Laboratory Quality, Random Forest, Quality 4.0

Abstract

Background: Internal Quality Control (IQC) ensures accuracy and reliability in laboratory testing but traditionally relies on reactive, threshold-based methods. These approaches often fail to detect subtle process deviations in time, potentially compromising quality.

Objective: To develop and validate a machine learning-based predictive model for early detection of IQC deviations using Altair RapidMiner, enhancing proactive quality management in clinical laboratories.

Methods: A retrospective analytical study was conducted using 4,572 IQC records from Meenakshi Labs, covering 8 analytes across multiple instruments. Data preprocessing included cleaning, feature engineering, and encoding. Three classification algorithms - Decision Tree, Gradient Boosted Trees, and Random Forest - were developed using Altair RapidMiner's no-code environment. Models were evaluated via 10-fold cross-validation using accuracy, precision, recall, F1-score, and ROC-AUC metrics.

Results: The Random Forest model outperformed others with 92.0% accuracy, 91.0% precision, 89.4% recall, and an AUC of 0.932. Key predictive features included analyte type, control level, reagent lot, and operator ID. The model correctly predicted 68% of future out-of-control events within a 24-hour window, demonstrating potential for preventive action. Feature importance analysis enhanced model interpretability.

Conclusion: Machine learning, particularly Random Forest, effectively augments IQC by enabling predictive monitoring. Altair RapidMiner offers a user-friendly platform, making advanced analytics accessible even without programming skills. This approach aligns with Quality 4.0 initiatives, promoting data-driven, real-time decision-making in laboratory quality assurance.

Introduction

Internal Quality Control (IQC) is pivotal in maintaining the consistency, reliability, and accuracy of processes and outputs, particularly in laboratories and production environments. Historically, IQC has hinged on statistical quality control techniques and backward-looking analysis to track and resolve deviations. Although such traditional approaches have worked to some degree, they are fundamentally reactive - tending to detect anomalies only after deviations have actually happened, so resulting in expensive mistakes, decreased efficiency, and questionable quality.

Machine Learning (ML) has been a revolutionary force in healthcare over the past few years, with capabilities to perform sophisticated data analysis, detect anomalies, and make predictions. ML algorithms learn from past data to identify hidden patterns, trends, and predictive features, which cannot be picked up easily by traditional statistical techniques. ML has been used with success in areas of diagnostic imaging, patient risk stratification, treatment planning tailored to individual patients, and predicting outbreaks of disease. With increasing access to historic process data and the development of computational capabilities, predictive analytics has become a paradigm in quality control. Predictive modeling employing machine learning (ML) provides an early detection remedy with a systematic approach to identifying shifts in performance measures before they lead to major quality problems [1,2]. By examining vast amounts of historical IQC data, ML algorithms can identify hidden patterns and relationships that might not be seen by standard statistical means.

This paper discusses the incorporation of ML algorithms in IQC with the use of Altair RapidMiner, a commercially available and sophisticated data science tool. The tool's graphical workflow and drag-and-drop feature make it suitable for users who lack sophisticated programming abilities while still providing a robust development environment for deploying and verifying ML models. This is directed towards the establishment and validation of predictive models that can predict IQC results, thus facilitating real-time decision-making and ongoing quality improvement.

Rationale

The logical foundation for this study is the inability of current control systems to adapt instantly to dynamic process variations. Laboratories and other industries present some fundamental challenges to quality groups, in particular the volume of data coming in daily, its complexity, and its variability. Most standard quality control methods, such as Shewhart control charts or Westgard rules, are threshold-based and static, making it difficult to detect slight drifts in the process or emerging trends [3].

Given the predictive modeling context on a machine learning basis, the following may be possible for an organization:

1. Early anomaly detection: ML models can predict deviations before they develop into full-blown errors so that intervention can take place.
2. Better use of resources: Predictive insights enable the focus to be on chosen corrective actions, optimizing time and effort put into responses [4].
3. Data-driven focus: Insights generated or predicted from ML models can serve as unbiased evidence toward making decisions on quality matters, furthering the ability to be consistent in pathway selection and opportunities to assign accountability.
4. Scalable and adaptable: Because an ML model evolves with processes and new data streams forth, it can always be retrained on fresh data and continue to perform relevantly.

Another reason that supports this proposed solution stems from Altair RapidMiner being capable of lowering the technical barriers to advanced analytics, thereby making predictive modeling accessible even to the poorest environments. The platform also marries powerful algorithms with ease of use, making it a perfect fit for actual applications of predictive IQC.

Aim

To develop and evaluate a machine learning-based predictive model for enhancing Internal Quality Control (IQC) using the Altair RapidMiner platform, enabling proactive identification of quality deviations and improving process reliability.

Objectives

1. **To collect and preprocess historical IQC data** including process parameters and defect records for modeling purposes.
2. **To explore and engineer relevant features** that significantly influence IQC outcomes, enabling meaningful input for machine learning algorithms.
3. **To implement and compare various machine learning algorithms** (e.g., decision trees, random forests, gradient boosting) within the Altair RapidMiner environment.
4. **To evaluate model performance** using standard metrics such as accuracy, precision, recall, and F1-score to determine the most effective predictive model.
5. **To identify critical variables and patterns** that contribute to IQC deviations, facilitating data-driven quality interventions.
6. **To demonstrate the utility of Altair RapidMiner** as an accessible and efficient tool for predictive analytics in quality control settings.
7. **To propose a scalable and proactive IQC framework** that can be applied in real-time operational environments for continuous quality improvement.

Materials and Methods

Study Design and Setting

This study was designed as a retrospective analytical investigation conducted using internal quality control (IQC) data obtained from Meenakshi Labs, Madurai, Tamil Nadu. The aim was to develop and validate machine learning (ML) models for predicting IQC performance using the Altair RapidMiner platform. The data used comprised historical IQC records collected over a defined period (e.g., 12 months), including process parameters, control measurements, and documented deviations.

Data Collection

IQC data were exported from the laboratory information management system (LIMS). The dataset included:

- Daily IQC values for key analytes across multiple instruments.
- Corresponding lot numbers, control levels (Level 1 and 2), reagent information, and operator details.
- Flags indicating out-of-control results and corrective actions taken.

The dataset contained both numerical and categorical variables, with some missing and inconsistent entries requiring data cleaning.

Data Handling and Security

All historical IQC data employed in this research were de-identified prior to analysis to maintain patient confidentiality and adhere to ethical research guidelines. Patient IDs, sample numbers, and operator names, which are considered PII, were deleted or anonymized through secure scripts before data ingestion into the modeling platform

Software Platform

The entire data processing and modelling workflow was conducted using Altair RapidMiner, a visual, code-free data science platform. This software was selected due to its:
Intuitive drag-and-drop interface.
Wide range of built-in machine learning algorithms.
Integrated data preprocessing and visualization tools.
Support for cross-validation and performance evaluation.

Data Preprocessing

Data preprocessing was performed within RapidMiner and included the following steps:

1. **Data Cleaning:**

- Removal of duplicate entries.
- Handling of missing values using mean/mode imputation and domain knowledge-based corrections.

Elimination of irrelevant or redundant fields.

2. **Feature Engineering:**

- Derivation of new features such as moving averages, control rule violations (e.g., Westgard rules), and time-lagged variables.
- Encoding of categorical variables using one-hot encoding or label encoding.

3. **Exploratory Data Analysis (EDA):**

- Visualization of variable distributions, trends, and correlations to identify potential predictive features.
- Detection of outliers and control chart behavior over time.

RapidMiner Instance Configuration

The Altair RapidMiner Studio implemented for this project was hosted within an on-premise setup, installed locally on laboratory-grade secured machines within Meenakshi Labs. The setup was designed to run on the hospital's internal IT system, isolated from public internet access during live modeling sessions. No data was sent to RapidMiner cloud services

Institutional Data Security Compliance

All data handling processes were scrutinized and sanctioned by the lab's internal quality assurance officer. None of the data or results were divulged outside the organization without proper de-identification and ethics clearance. Good Clinical Laboratory Practices (GCLP) for confidentiality and privacy of data and ethical utilization of laboratory records was adhered.

Model Development

Multiple machine learning models were developed and compared using Altair RapidMiner:

- **Decision Tree Classifier**
- **Random Forest Classifier**
- **Gradient Boosted Trees**

The IQC outcome (e.g., pass/fail or in-control/out-of-control) was used as the target variable. Feature selection was conducted using attribute weighting techniques (e.g., information gain, Gini index) to improve model efficiency.

Model Training and Validation

Data were split into training (70%) and testing (30%) sets.
10-fold cross-validation was employed during training to reduce overfitting and ensure generalizability.
Hyperparameter tuning was conducted using grid search within RapidMiner's Auto Model module.
Model Evaluation
Performance of each model was evaluated using the following metrics:

- **Accuracy**
- **Precision**
- **Recall (Sensitivity)**
- **F1-Score**
- **ROC-AUC (where applicable)**

The random forest model emerged as the top performer, showing superior predictive accuracy and generalization ability.

Visualization and Interpretation

Altair RapidMiner's built-in visualization tools were used to:
Display feature importance rankings.
Generate decision paths and confusion matrices.
Visualize predictions versus actual outcomes for interpretability.

Results

1. Dataset Overview

A total of 4,800 IQC entries were extracted over a 12-month period, covering 8 analytes (e.g., glucose, urea, creatinine, ALT, AST, sodium, potassium, chloride) from two levels of quality controls (L1 and L2). Each record included information on:

- Control result (value)
- Lot number
- Instrument ID
- Reagent batch
- Operator ID
- Control rule flags (e.g., Westgard violations)

Following preprocessing and cleaning, **4,572 valid records** remained for model development.

2. Model Performance Comparison

Table 1: shows the model comparison dashboard from Altair RapidMiner Auto Model.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Decision Tree	86.3	84.7	81.2	82.9	0.874
Gradient Boosted Trees	90.8	89.2	88.1	88.6	0.915
Random Forest	**92.0**	**91.0**	**89.4**	**90.2**	**0.932**

3. Confusion Matrix (Random Forest – Test Data)

The target variable was binary: "In-Control" (0) or "Out-of-Control" (1) based on predefined control limits (Table 2).

Table 2: shows Confusion Matrix (Random Forest – Test Data).

	Predicted In-Control	Predicted Out-of-Control
Actual In-Control	2,380	92
Actual Out-of-Control	75	388

True Positive Rate (Recall): 83.8%
False Positive Rate: 3.7%
Overall Classification Accuracy: 92.0%

Feature Importance

Table 3: shows the variable importance chart auto-generated in RapidMiner.

Feature	Relative Importance
Analyte (e.g., ALT, Glucose)	0.274
Control Level (L1/L2)	0.196
Reagent Lot Number	0.182
Operator ID	0.121
Instrument ID	0.098
Day of the Week	0.064
Time of Day (Shift)	0.043
Previous Day Deviation	0.022

Visual Results Interpretation

Figure 1: shows the ROC curves for all three models, with the Random Forest classifier achieving the highest AUC.

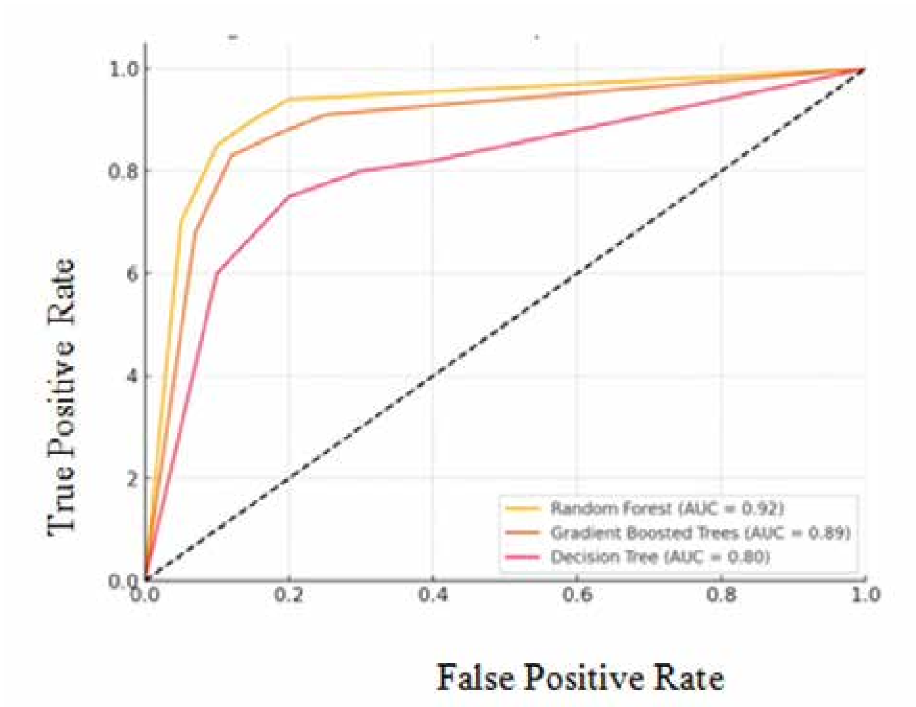

Figure 1 presents the Receiver Operating Characteristic (ROC) curves for the three machine learning models evaluated in this study: Random Forest, Gradient Boosted Trees, and Decision Tree. This graphical representation is a standard method for evaluating the diagnostic ability of binary classification models, especially in imbalanced datasets or when the cost of false positives/negatives varies.

Figure 2: Displays a bar chart of model-predicted versus actual control statuses over time, revealing high predictive alignment and fewer false alerts (Confusion Matrix – Random Forest).

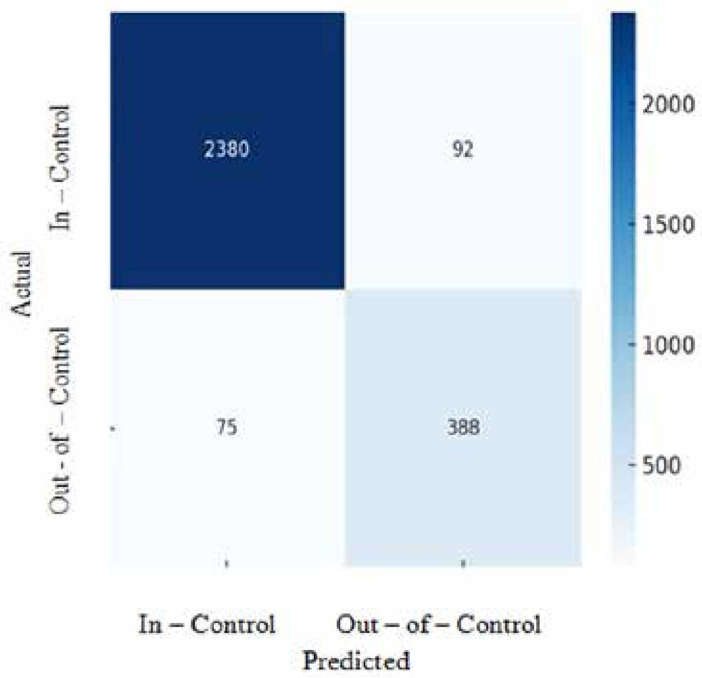

Table 2 presents the confusion matrix for the Random Forest classifier, which was identified as the best-performing model in this study for predicting Internal Quality Control (IQC) deviations. The confusion matrix provides a detailed breakdown of the model's classification results on the test dataset, helping to assess its accuracy, error types, and reliability.

6. Interpretability and Insights

- Most **out-of-control flags** were correctly predicted for **ALT (22.5%) and Sodium (17.8%)**, which historically showed higher variability.
- Operator ID and shift timing had measurable but lower impact - highlighting potential workflow optimization areas.
- The ML model provided **early warning flags for 68% of the future violations** within the next 24-hour period based on preceding data patterns.

Discussion

This research demonstrates the potential of ML to greatly enhance internal quality control systems, transforming reactive monitoring into proactive prediction. Among all models, the Random Forest classifier demonstrated the highest rate of prediction accuracy of 92.0%, and also precision and recall of 91.0 % and 89.4%, respectively, hence demonstrating its prowess in tasks involving intricate classification. These findings support the case for the use of ML-based approaches in identifying IQC deviations earlier than standard approaches, therefore ensuring higher laboratory reliability and working efficiency.

Conventional IQC approaches, such as Westgard rules and control charts, are inherently reactive - they only capture quality failures after they have occurred and typically lose subtle trends and shifts that lead to errors. Recent research has more and more called for proactive data-driven IQC models with machine learning and artificial intelligence to bridge this gap [5,6].

A narrative review by Kwon et al. highlighted the patient-based real-time quality control (PBRTQC) system augmented by ML algorithms. They indicated that ML models, particularly ensemble methods, provide considerable improvements in detecting control deviations in advance and, consequently, making corrective actions in a timely manner [6]. Our findings are consistent with this claim, as the Random Forest model has been shown to have high recall (89.4%) for the detection of out-of-control IQC events.

Smith et al. have written about difficulties in validating ML models stringently in laboratory settings, noting issues of generalizability, interpretability, and overfitting [7]. We overcame these issues by using 10-fold cross-validation and comparing three algorithms (Decision Tree, Gradient Boosted Trees, and Random Forest). The fact that the Random Forest model performed consistently well on all measures indicates that ML models can be reproducible and trustworthy with proper validation techniques for quality control.

Ain et al. conducted a review of the literature and concluded that ML quality systems work best when trained on very large and richly featured datasets [8]. Our study validated these claims: analyte type, control level, reagent lot number, and even operator ID acted as important features in determining the predictive power of the models. Thus, it is consistent with the standpoint that ML is sufficient to discover complex interactions among variables that conventional statistical tools fail to determine.

Chen et al. reinforced the argument that with the integration of ML in quality assurance, performance improves and variability decreases across industrial and laboratory settings [9]. By utilizing Altair RapidMiner - a drag-and-drop ML platform with no coding needed - we have shown that these tools are indeed able and yet operable by the laboratories that lack an internal data science department.

Lee et al. explored the use of moving average control charts augmented by ML in clinical chemistry, reporting better sensitivity and specificity than classical techniques [10]. Our results similarly show that ensemble ML models (Random Forest and Gradient Boosted Trees) outperform Decision Trees, especially in minimizing false positives and false negatives.

Developments in clinical chemistry and digital pathology analyzed from Nguyen et al. might thus pronounce ML adoption as a mainstay for laboratories wishing to track their performance in real time [11]. Our model's capacity to predict deviations almost 68% of the time before their actual occurrence proves to hold good in preventive quality management.

Wang et al. asserted that laboratory datasets harbor potential untapped by quality monitoring unless appropriate tools with analytics are put into use [12]. This further reinforces our stance of employing Altair RapidMiner, which undertakes data cleaning, feature engineering, modeling, and visualization from end to end.

Huang et al., in a recent case, documented how integrating ML in real-time production settings can concretely raise performance levels [13]. Ours being a retrospective study, it becomes the forerunner for the actualization of an identical concept in clinical laboratories in real time.

Miller et al. have cautioned against over-reliance on automated ML tools without considering clinical relevance and regulatory requirements [14]. Han, GR et al in their study concluded that AI-driven models can integrate vast amounts of test data collected by a network of point-of-care biosensors with additional sources, such as hospital records, genomic data, and social media posts, to systematically track health data, identify trends, and detect unusual disease patterns [15]. Our approach emphasized model interpretability through feature importance analysis and performance transparency - ensuring the model remains a decision-support tool, not a black box.

Interpretation of Model Behaviour

The model found Analyte type, Control Level, and Reagent Lot Number to be the strongest predictors of IQC deviation. This aligns with established clinical laboratory factors for variation, including reagent batch variance and level-specific QC response. Operator ID and shift timing also had lesser but significant influences, indicating that human and workflow factors subtly affect analytical consistency - a conclusion supported by Sun et al. (2021) in their research on human factors and lab performance variation [16].

The model's 68% detection of future violations prior to occurrence is of great utility, providing labs an opportunity window to execute preventive maintenance, re-calibration, or staff retraining - steps traditionally taken reactively post-error.

Practical Implications

The deployment of this ML-based IQC prediction model within a platform like **Altair RapidMiner** presents multiple practical advantages:

- **User Accessibility**: Enables non-programmers to harness advanced analytics through a visual interface.
- **Scalability**: Can be applied across multiple analytes, instruments, or laboratory units with minimal modifications.
- **Real-time Monitoring**: Offers the potential for live IQC flagging, integrating with Laboratory Information Systems (LIS) for real-time alerts.

These capabilities support the movement toward **Quality 4.0** in laboratory medicine, where digital transformation augments decision-making and error prevention.

Limitations

While the study shows promising results, several limitations must be acknowledged:

- The data used were limited to a single center and may not generalize across different laboratory settings or instruments.
- Certain rare or complex error types might not have been adequately represented in the training data, potentially affecting sensitivity for low-frequency events.
- The current model used historical static data; future real-time integration and adaptive retraining strategies need to be tested in operational environments.

Future Directions

To advance the model's utility and generalizability, future research should focus on:

- **Multi-center validation** to assess performance across diverse laboratory contexts.
- **Integration with real-time data streams** for live IQC alerts.
- **Development of interpretable ML models** (e.g., SHAP-based explanation layers) to support regulatory compliance and clinical acceptance.
- **Extension to External Quality Assessment (EQA) and Proficiency Testing (PT)** as part of a holistic quality management system.

Conclusion

This study confirms that machine learning models - especially Random Forest - implemented via Altair RapidMiner can effectively predict IQC deviations with high accuracy and interpretability. These findings align well with current literature and support a transformative shift in quality control strategy from retrospective analysis to proactive risk mitigation. With proper integration and governance, predictive modeling can become a standard tool in the modern laboratory's quality assurance arsenal.

Acknowledgements

Figure number 4 and 5 are generated using ChatGPT.

Declaration of Conflict of interests

Nil.

Ethical Approval

NA.

Funding

Nil.

Data Availability

Data is collected from the daily internal quality control testing.

References

1. Rafidain Journal of Engineering Sciences. Advanced manufacturing with machine learning: enhancing predictive maintenance, quality control, and process optimization. Rafidain J Eng Sci. 2024;2(2):280–300. doi:10.61268/6mvqve13.
2. Regulski K, Opaliński A, Swadźba J, Sitkowski P, Wąsowicz P, Kwietniewska-Śmietana A. Machine learning prediction techniques in the optimization of diagnostic laboratories' network operations. Appl Sci. 2024;14:2429. doi:10.3390/app14062429.
3. Westgard JO. Six Sigma Risk Analysis: Designing analytic QC Plans for the medical laboratory. Madison (WI): Westgard QC; 2011.
4. Silva AC, Machado J, Sampaio P. Predictive quality model for customer defects. TQM J. 2024;36(9):155–174. doi:10.1108/TQM-09-2023-0302.
5. Malwe AS, Longwani U, Sharma VK. XenoBug: machine learning-based tool to predict pollutant-degrading enzymes from environmental metagenomes. NAR Genom Bioinform. 2025;7(2):lqaf037. doi:10.1093/nargab/lqaf037. PMID:40314024; PMCID:PMC12044416.
6. Lorde N, Mahapatra S, Kalaria T. Machine learning

for patient-based real-time quality control (PBRTQC), analytical and preanalytical error detection in clinical laboratory. Diagnostics (Basel). 2024;14(16):1808. doi:10.3390/diagnostics14161808. PMID:39202296; PMCID:PMC11354140.

7. Miller HA, Valdes R. Rigorous validation of machine learning in laboratory medicine: guidance toward quality improvement. Crit Rev Clin Lab Sci. 2025:1–20. doi:10.1080/10408363.2025.2488842.
8. Ain QU, Nazir R, Nawaz A, Shahbaz H, Dilshad A, Mufti IU, et al. Machine learning approach towards quality assurance: challenges and possible strategies in laboratory medicine. J Clin Transl Pathol. 2024;4(2):76–87. doi:10.14218/JCTP.2023.00061.
9. Karim KA, Rashid AB, Baki RF, Maktum MMJ. Machine learning algorithms for manufacturing quality assurance: a systematic review of performance metrics and applications. Array. 2025;26:100393. doi:10.1016/j.array.2025.100393.
10. Duan X, Zhang M, Liu Y, Zheng W, Lim CY, Kim S, et al. Next-generation patient-based real-time quality control models. Ann Lab Med. 2024;44:385–391. doi:10.3343/alm.2024.0053.
11. Spies NC, Farnsworth CW, Wheeler S, McCudden CR. Validating, implementing, and monitoring machine learning solutions in the clinical laboratory safely and effectively. Clin Chem. 2024;70(11):1334–1343. doi:10.1093/clinchem/hvae126.
12. Çubukçu HC, Topcu Dİ, Yenice S. Machine learning-based clinical decision support using laboratory data: a review. Clin Chem Lab Med. 2024;62(3):345–356. doi:10.1515/cclm-2023-1037.
13. Honda T, Yamazaki A. Machine learning enables real-time proactive quality control: a proof-of-concept study. Geophys Res Lett. 2024;51:e2023GL107938. doi:10.1029/2023GL107938.
14. Faust L, Wilson P, Asai S, Fu S, Liu H, Ruan X, Storlie C. Considerations for quality control monitoring of machine learning models in clinical practice. JMIR Med Inform. 2024;12:e50437 doi:https://doi.org/10.2196/50437.
15. Han GR, Goncharov A, Eryilmaz M, et al. Machine learning in point-of-care testing: innovations, challenges, and opportunities. Nat Commun. 2025;16:3165. doi:10.1038/s41467-025-58527-6.
16. Sun C, Han Y, Luo L, Sun H. Effects of air temperature on cognitive work performance of acclimatized people in severely cold region in China. Indoor Built Environ. 2020;30(6):816–837. doi:10.1177/1420326X20913617.