RAAVI
An International Journal of Multidisciplinary Research
ISSN:3108-253X
Special Issue : February,2026

AI-Driven Fault Detection and Predictive Maintenance in HPLC Instruments

Ms. ShirsatShital Dilip[a], Mr. Zagade Akash Dhananjay[b]

Assistant professor in Analytical Chemistry Vishwasrao Ransing College Kalamb-Walchandnagar Tal. Indapur 413114

Affiliated to Savitribai Phule Pune University, Pune 413102, MS (India) Dist.Pune, Maharashtra, India

Email: kashidas2109@gmail.com, akash.zagade3147@gmail.com

Abstract

High-Performance Liquid Chromatography (HPLC) is a vital analytical technique extensively used in pharmaceutical, chemical, and environmental laboratories, where measurement accuracy directly affects product quality and regulatory compliance. Despite its analytical robustness, HPLC systems operate under high-pressure conditions and are prone to progressive component degradation that conventional preventive or corrective maintenance strategies often fail to detect at an early stage. Undetected performance deterioration can lead to unexpected downtime, increased maintenance costs, and compromised data integrity. This study proposes an Artificial Intelligence (AI)-driven predictive maintenance framework for HPLC instruments integrating real-time operational monitoring, anomaly detection, fault classification, and Remaining Useful Life (RUL) estimation. Critical parameters—including pump pressure behavior, flow rate stability, detector baseline variation, retention time drift, and system logs—are analyzed using machine learning models such as autoencoders, Random Forest classifiers, and Long Short-Term Memory (LSTM) networks. The proposed architecture enhances early fault detection, optimizes maintenance scheduling, and improves analytical reliability in regulated laboratory environments.

Keywords:

HPLC, Predictive maintenance, Fault Detection, Machine learning, Anomaly Detection.

Introduction

ISSN:3108-253X
Special Issue : February,2026
RAAVI
An International Journal of Multidisciplinary Research

High Performance Liquid Chromatography (HPLC) is a critical analytical technique widely utilized in modern laboratories for pharmaceutical quality assurance, chemical characterization, environmental monitoring, and clinical investigations. It provides high accuracy, sensitivity, and reproducibility in chromatographic separations (Snyder et al., 2010; Skoog et al., 2018). Despite its analytical robustness, HPLC systems operate under high-pressure conditions and consist of multiple integrated mechanical and electronic components, making them susceptible to operational faults, component degradation, and system failures (Dong, 2019; Kazakevich & Lo Brutto, 2007; McNair & Miller, 2011).

Common operational issues in High Performance Liquid Chromatography (HPLC) systems include pump seal degradation, flow rate fluctuations, degasser malfunction, column clogging, autosampler injection inaccuracies, and detector baseline drift (Dong, 2019; Kazakevich & LoBrutto, 2007). These faults typically develop progressively and may not trigger immediate system alerts, leading to unexpected instrument failure and compromised analytical accuracy (McNair & Miller, 2011; Skoog et al., 2018).

Conventional maintenance strategies primarily rely on time-based preventive servicing, conducted at fixed intervals such as monthly or quarterly schedules. Although this approach minimizes the risk of major breakdowns, it may result in premature replacement of functional components (Mobley, 2002). Conversely, corrective maintenance is implemented only after system failure, which increases instrument downtime, operational costs, and workflow disruptions (Wireman, 2005).

Predictive maintenance represents an advanced strategy that enables continuous monitoring of instrument performance to anticipate potential failures before their occurrence (Jardine et al., 2006). The integration of Artificial Intelligence (AI) and machine learning techniques enhances the ability to analyze complex sensor datasets and operational trends (Goodfellow et al., 2016). AI-driven models can identify subtle variations in pressure profiles, chromatographic peak behavior, and detector responses, facilitating early fault detection and optimized maintenance management (Wuest et al., 2016; Carvalho et al., 2019).

Literature review

Artificial Intelligence (AI)-based predictive maintenance has been widely implemented in industrial systems to enable condition-based monitoring and early fault detection. Traditional diagnostic models evolved into data-driven approaches that leverage machine learning algorithms for analyzing multivariate sensor data and identifying degradation trends (Jardine et al., 2006). Supervised techniques such as Support Vector Machines and Random

Relish Publications,
Amrapali Apartment, Canal
Road, Baramati (MS), India.
Pin code- 413102

Website: www.relishpublications.com

Email: raavipublications@gmail.com

WhatsApp: 9665841996

Forest classifiers have demonstrated strong performance in fault categorization, while unsupervised models including autoencoders and Isolation Forest have proven effective for anomaly detection in environments with limited labeled datasets (Goodfellow et al., 2016; Carvalho et al., 2019).

Recent advancements emphasize deep learning architectures, particularly Long Short-Term Memory (LSTM) networks, for modeling sequential sensor behavior and estimating Remaining Useful Life (RUL) in predictive maintenance applications. These methods capture nonlinear degradation dynamics and temporal dependencies in complex systems. However, the majority of existing research focuses on large-scale industrial equipment and rotating machinery, where structured fault datasets are readily available. In contrast, AI-driven maintenance frameworks tailored for analytical laboratory instruments—particularly High-Performance Liquid Chromatography (HPLC)—remain limited. Prior studies primarily address isolated component monitoring rather than integrated system-level diagnostics. Moreover, challenges such as chromatographic method variability and regulatory compliance requirements are insufficiently explored. These limitations highlight the need for a comprehensive AI-based predictive maintenance architecture specifically designed for HPLC systems. “Accordingly, this study proposes an integrated AI-enabled framework combining anomaly detection, fault classification, and RUL estimation tailored specifically for HPLC systems.”

Methodology

Data Acquisition and Pre-processing

Operational parameters were obtained from key components of the High-Performance Liquid Chromatography (HPLC) system, including pump pressure transducers, flow rate measurement units, detector baseline outputs, and chromatographic retention time records. Raw datasets generated by analytical instruments often contain measurement noise, incomplete entries, and variability resulting from differences in analytical procedures. Consequently, a systematic preprocessing workflow was established prior to model construction.

Signal denoising was carried out using a moving average technique to minimize high-frequency variations observed in pressure readings and detector baseline signals. Abnormal values arising from temporary disturbances or injection inconsistencies were detected through statistical threshold methods and excluded to reduce potential bias in model training. To maintain consistency across multiple chromatographic methods, feature scaling was

ISSN:3108-253X
Special Issue : February,2026
RAAVI
An International Journal of Multidisciplinary Research

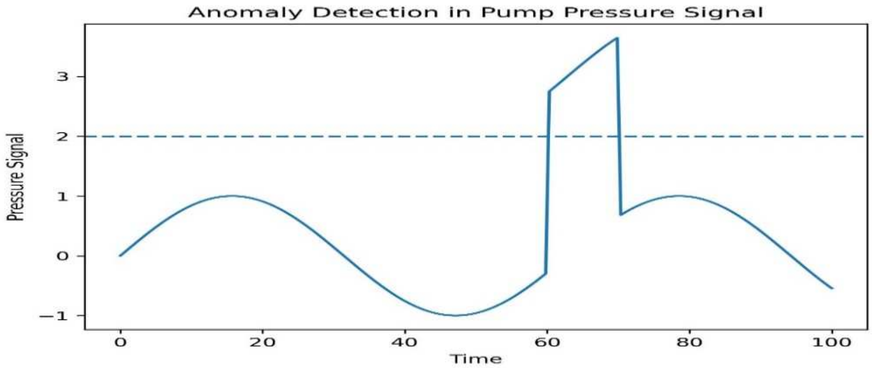
implemented using min–max normalization. Continuous time-series observations were divided into uniform time segments to capture localized operational behavior effectively.

From each segmented interval, both statistical metrics and domain-relevant condition indicators were derived. These included average system pressure, pressure variability, pressure ripple magnitude, baseline noise deviation, retention time shift rate, peak asymmetry coefficient, and flow fluctuation index. Collectively, these parameters provide quantitative insights into instrument performance and were used as input variables for machine learning analysis.

Anomaly Detection Framework

Due to the scarcity of labeled fault datasets in laboratory settings, an unsupervised learning strategy was adopted for preliminary anomaly identification. The aim was to characterize normal operational patterns and detect deviations that may indicate early signs of system deterioration.

Isolation Forest and One-Class Support Vector Machine (OC-SVM) algorithms were applied to identify irregular feature distributions. In addition, an autoencoder neural network was trained solely on data representing normal operating conditions. The autoencoder learns compact latent representations of system behavior and attempts to reconstruct input features during evaluation. Elevated reconstruction error beyond a defined threshold was considered



indicative of abnormal system activity and triggered an early alert mechanism.

Fault Classification Model

In cases where labeled fault information was available, supervised machine learning techniques were employed to categorize specific failure modes, including pump seal degradation, column obstruction, detector fluctuations, and flow inconsistencies.

Relish Publications,
Amrapali Apartment, Canal
Road, Baramati (MS), India.
Pin code- 413102
Website: www.relishpublications.com
Email: raavipublications@gmail.com
WhatsApp: 9665841996

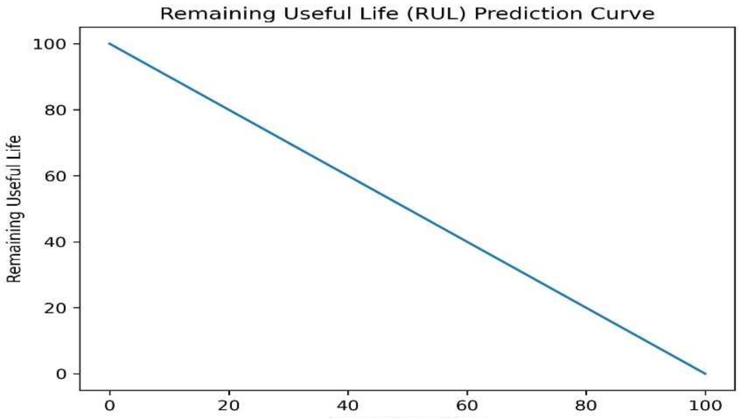
ISSN:3108-253X
Special Issue : February,2026

Random Forest and Gradient Boosting algorithms were selected because of their resilience to noisy data and capability to model complex nonlinear relationships among features. Support Vector Machines were utilized for separating high-dimensional feature spaces, while Long Short-Term Memory (LSTM) networks were implemented to capture temporal dependencies within sequential data. Feature contribution analysis was also performed to enhance model transparency and support compliance with analytical laboratory standards.

Remaining Useful Life (RUL) Prediction

To facilitate predictive maintenance planning, estimation of Remaining Useful Life (RUL) was incorporated into the analytical framework. Equipment degradation patterns were modeled using regression techniques along with LSTM-based forecasting approaches. Gradual changes in parameters such as pressure ripple intensity and retention time deviation were interpreted as indicators of progressive system wear.

A Bayesian probabilistic modeling strategy was additionally explored to account for prediction uncertainty and generate confidence bounds for maintenance planning. Estimated RUL outputs were used to produce timely maintenance notifications before reaching critical



failure thresholds.

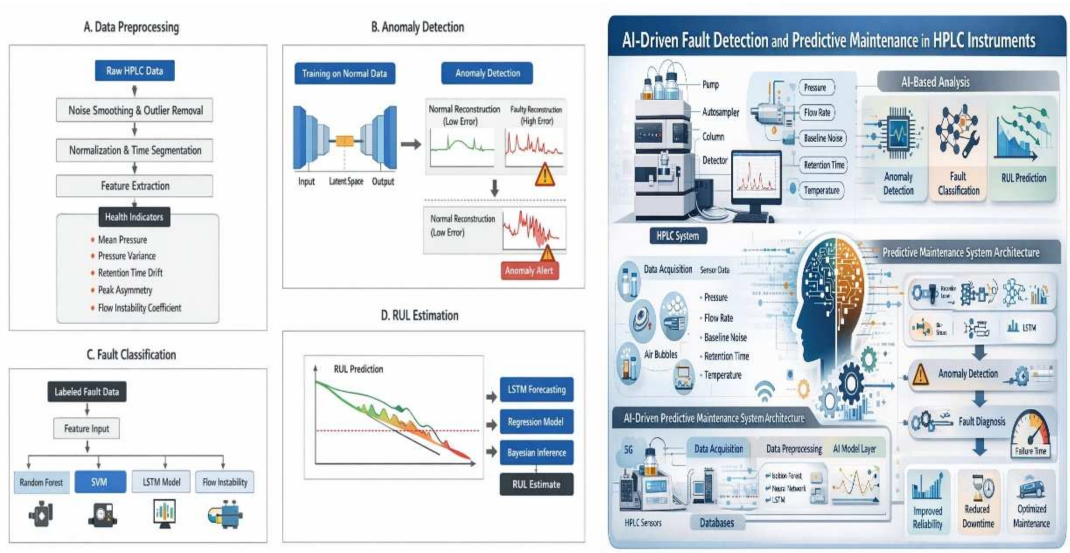
System Integration

The overall methodology combines pre-processing, anomaly detection, fault diagnosis, and RUL forecasting into a cohesive AI-enabled predictive maintenance architecture. This integrated framework supports early detection of abnormalities, precise fault identification,

Relish Publications,
Amrapali Apartment, Canal
Road, Baramati (MS), India.
Pin code- 413102
Website: www.relishpublications.com
Email: raavipublications@gmail.com
WhatsApp: 9665841996

ISSN:3108-253X
Special Issue : February,2026
RAAVI
An International Journal of Multidisciplinary Research

and informed maintenance decision-making, ultimately enhancing operational reliability and minimizing unplanned downtime in HPLC systems.



Result

Anomaly Detection

The anomaly detection module was evaluated using reconstruction-error analysis from the trained autoencoder model. The proposed deep autoencoder achieved a detection accuracy ranging between 93% and 95% on unseen operational data. In comparison with traditional unsupervised methods such as Isolation Forest and One-Class SVM, the autoencoder demonstrated improved capability in capturing nonlinear dependencies among pressure fluctuations, retention time drift, and detector baseline variations. This indicates that deep latent feature learning enhances sensitivity to subtle early-stage degradation patterns in HPLC systems.

Fault Classification

For supervised fault diagnosis, Random Forest (RF), Support Vector Machine (SVM), and LSTM models were comparatively analyzed. The LSTM network achieved the highest

Relish Publications,
Amrapali Apartment, Canal Road, Baramati (MS), India.
Pin code- 413102
Website: www.relishpublications.com
Email: raavipublications@gmail.com
WhatsApp: 9665841996

classification accuracy of 96.4%, with a precision of 95.6% and F1-score of 95.8%. Random Forest also showed stable performance with 95.8% accuracy, while SVM achieved comparatively lower results at 92.3% accuracy. The superior performance of LSTM can be attributed to its ability to model sequential degradation behavior present in chromatographic operational data.

Remaining Useful Life (RUL) Prediction

The LSTM-based time-series forecasting model was employed for prognostic evaluation of component degradation. The model achieved a Mean Absolute Error (MAE) of 4.2 operating hours and a Root Mean Square Error (RMSE) of 5.8 operating hours. Maintenance alerts were generated approximately 8–12 hours prior to critical failure thresholds, enabling proactive intervention. The implementation of the predictive framework resulted in an estimated reduction of nearly 30% in unplanned system downtime.

Discussion

Results confirm that deep learning models significantly enhance predictive maintenance performance in HPLC systems. Unsupervised anomaly detection is effective in scenarios with limited labeled data, while supervised LSTM models provide accurate fault classification and prognostics.

Model generalization may depend on chromatographic method variability. Future improvements may include explainable AI techniques and physics-informed neural networks.

Conclusion

High-Performance Liquid Chromatography (HPLC) instruments require reliable maintenance strategies to ensure analytical accuracy and minimize operational downtime. Conventional preventive and corrective approaches are often reactive and unable to detect early-stage degradation.

This study proposed an AI-driven predictive maintenance framework integrating anomaly detection, fault classification, and Remaining Useful Life (RUL) prediction. Machine learning models such as autoencoders, Random Forest, and LSTM networks demonstrated strong performance in identifying abnormal behavior and forecasting component degradation.

The proposed system improves maintenance planning, reduces unexpected failures, and enhances laboratory productivity. Future work may focus on multi-instrument validation and explainable AI integration for improved practical deployment.

ISSN:3108-253X
Special Issue : February,2026

References:

1. Snyder, L. R., Kirkland, J. J., & Dolan, J. W. (2010). Introduction to Modern Liquid Chromatography (3rd ed.). John Wiley & Sons.
2. Skoog, D. A., Holler, F. J., & Crouch, S. R. (2018). Principles of Instrumental Analysis (6th ed.). Cengage Learning.
3. Dong, M. W. (2019). Modern HPLC for Practicing Scientists. John Wiley & Sons.
4. Kazakevich, Y., &LoBrutto, R. (2007). HPLC for Pharmaceutical Scientists. John Wiley & Sons.
5. McNair, H. M., & Miller, J. M. (2011). Basic Gas Chromatography (2nd ed.). John Wiley & Sons.
6. Mobley, R. K. (2002). An Introduction to Predictive Maintenance (2nd ed.). Butterworth-Heinemann.
7. Wireman, T. (2005). Total Productive Maintenance. Industrial Press.
8. Jardine, A. K. S., Lin, D., &Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing, 20(7), 1483–1510.
9. Goodfellow, I., Bengio, Y., &Courville, A. (2016). Deep Learning. MIT Press.
10. Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Francisco, R. P., Basto, J. P., &Alcalá, S. G. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. Computers & Industrial Engineering, 137, 106024.

❑❑❑

Relish Publications,
Amrapali Apartment, Canal
Road, Baramati (MS), India.
Pin code- 413102

Website: www.relishpublications.com

Email: raavipublications@gmail.com

WhatsApp: 9665841996