Artificial Intelligence and Machine Learning Review
Scipublication
DOI: 10.69987/AIMLR.2024.50205

AI-Driven Reliability Algorithms for Medical LED Devices: A Research Roadmap

Zonglei Dong
MBA & MS in Finance, University of Texas at Dallas, TX, USA

Keywords

LED reliability prediction, machine learning algorithms, medical device quality control, predictive maintenance

Abstract

This research presents a comprehensive framework for artificial intelligence-driven reliability prediction and quality control algorithms specifically designed for medical-grade LED devices. The study addresses critical challenges in medical LED reliability assessment through hybrid machine learning approaches that combine physics-informed neural networks with advanced anomaly detection systems. Our methodology integrates multi-parameter health indicators, real-time monitoring capabilities, and predictive maintenance algorithms to achieve reliable remaining-life prediction with a 3.2% mean absolute percentage error (MAPE) while reducing required qualification testing from approximately 6,000 hours to about 1,500 hours (≈75% reduction). The proposed framework is designed to align with U.S. FDA Quality System Regulation (21 CFR Part 820) principles and common infection control objectives in healthcare environments, supporting safer deployment of LED-based medical devices in healthcare facilities. Implementation results demonstrate significant improvements in device lifetime prediction, quality control efficiency, and operational cost reduction, advancing both technological innovation and public health safety standards in American healthcare systems.

1. Introduction

1.1 Research Background

Medical-grade LED devices have become integral components in modern healthcare infrastructure, spanning applications from surgical lighting and photobiomodulation therapy to UV-C disinfection systems and diagnostic imaging equipment. The critical nature of these applications demands unprecedented reliability standards that current testing methodologies struggle to achieve efficiently. Traditional reliability assessment protocols, primarily based on LM-80 and TM-21 standards, require extensive testing periods exceeding 6,000 hours while limiting predictive extrapolation capabilities to merely six times the test duration. This constraint creates significant bottlenecks in medical device qualification processes, delaying the deployment of innovative LED technologies in healthcare settings.

The convergence of artificial intelligence with semiconductor reliability physics presents transformative opportunities for addressing these limitations. Recent advancements in machine learning algorithms, particularly in deep neural networks and Bayesian inference methods, enable the accurate prediction of degradation using limited early-stage data. These algorithmic innovations align directly with the U.S. Department of Energy's initiative for sustainable healthcare facilities and the FDA's evolving framework for AI-enabled medical devices. The integration of AI-driven approaches not only accelerates device qualification but also enhances compliance with emerging regulatory requirements for algorithmic transparency and data traceability in medical applications.

1.2 Research Objectives

This research aims to develop and validate a comprehensive AI-driven framework for predicting medical LED reliability and quality control, addressing both technological advancement needs and regulatory compliance requirements. The primary objective is to establish hybrid machine learning architectures that integrate physics-based degradation models with data-driven pattern recognition to achieve superior prediction accuracy while maintaining the interpretability essential for medical device certification. The framework specifically targets reducing qualification testing duration from traditional 6,000+ hours to about 1,500 hours (≈75% reduction) while improving prediction accuracy beyond current industry standards.

The secondary objectives focus on developing multi-parameter health indicators that synthesize electrical, thermal, and optical measurements into composite reliability metrics suitable for real-time monitoring in deployed medical devices. This approach enables predictive maintenance strategies that prevent unexpected failures in critical healthcare applications while optimizing operational efficiency. The research additionally addresses the need for uncertainty quantification in AI predictions, providing confidence bounds essential for safety-critical medical applications.

Through alignment with FDA medical device quality systems and CDC infection control strategies, this work contributes to strengthening the technological foundation for the domestic manufacturing of high-performance medical LEDs, advancing U.S. competitiveness in medical device innovation, and aligning with national supply-chain resilience goals. This work addresses critical operational needs in U.S. healthcare settings, including hospital infection control, intelligent UV-C disinfection scheduling, and predictive maintenance of surgical lighting and phototherapy systems, with the goal of improving patient safety, reducing unplanned downtime, and lowering the cost of clinical engineering support.

2. Related Work

2.1 LED Reliability Prediction Methods

A. Traditional Statistical Approaches

Statistical reliability modeling for LED devices has historically relied on accelerated life testing combined with extrapolation techniques based on empirical degradation models. Yi et al. [1] modeled temperature behavior in display lighting modules, illustrating how thermal stress prediction can support downstream reliability analysis. We adapt this idea to high-power medical LED assemblies, which experience more stringent duty cycles. These traditional methods typically employ Arrhenius relationships for temperature acceleration and inverse power law models for current stress factors. The exponential decay model remains widely used for predicting lumen maintenance, although its accuracy diminishes significantly when extrapolating beyond the tested conditions.

Sutharssan et al. [2] conducted comprehensive prognostics studies on high-power LEDs, revealing that junction temperature variations of merely 10°C can alter device lifetime by factors exceeding two. Their analysis of catastrophic and degradation failure mechanisms identified wire bond fatigue, die attach delamination, and phosphor degradation as primary failure modes requiring distinct modeling approaches. The limitations of purely statistical methods become apparent when addressing multiple concurrent degradation mechanisms, particularly in medical applications where both gradual light output decay and sudden catastrophic failures pose significant risks.

B. Machine Learning Algorithms

Machine learning approaches have revolutionized LED reliability prediction by capturing complex nonlinear relationships that traditional statistical models cannot adequately represent. Belloni and Gärtner [3] explored challenges specific to medical LED applications, highlighting that adaptive, nonlinear models are better suited than simple linear regression to capture temperature- and current-dependent degradation behavior in diagnostic and therapeutic devices. The evolution toward deep learning architectures has enabled unprecedented prediction accuracy by automatically extracting features from high-dimensional sensor data. Kuo et al. [4] developed automated inspection systems for surface mount LED devices, achieving defect detection rates of 98.7% using convolutional neural networks combined with morphological image processing. These advances in pattern recognition directly translate to the identification of degradation signatures, enabling early failure detection during initial operational periods. The integration of recurrent neural networks, particularly Long Short-Term Memory (LSTM) architectures, has proven especially effective for modeling time-series degradation, capturing temporal dependencies that static models often overlook.

2.2 Quality Control in Medical LED Manufacturing

A. Automated Optical Inspection

Automated optical inspection systems have emerged as critical quality control tools in medical LED manufacturing, replacing subjective manual inspection with objective, reproducible measurements. Ibrahim et al. [5] presented comprehensive frameworks integrating machine learning with digital twin concepts for LED degradation analysis, demonstrating how real-time inspection data feeds predictive models for enhanced reliability assessment. Their approach combines high-resolution imaging with spectral analysis to detect microscopic defects that are invisible to conventional inspection methods, achieving defect identification accuracies exceeding 96% for critical parameters that affect medical device performance.

Liao et al. [6] established guidelines for AOI system development, emphasizing the importance of multi-angle illumination and adaptive thresholding algorithms for medical-grade component inspection. Their systematic approach to lighting configuration, camera positioning, and image processing pipeline design ensures consistent defect detection across varying LED package types and substrate materials. The integration of these inspection systems with manufacturing execution systems enables real-time quality tracking and the implementation of immediate corrective actions.

B. Real-time Monitoring Systems

Real-time monitoring capabilities represent a paradigm shift from periodic inspection to continuous quality assurance throughout the manufacturing process. Meneghini et al. [7] analyzed reliability design choices in high-power LEDs, emphasizing the need for continuous monitoring under realistic operating stress. We build on that motivation and implement a low-latency monitoring layer that runs on embedded hardware.The implementation of edge computing architectures enables sophisticated algorithms to operate directly on production equipment, reducing latency and allowing for immediate responses to detected anomalies.

Abd Al Rahman and Mousavi [8] conducted extensive reviews of automatic optical inspection methods in electronics manufacturing, identifying key technological trends toward intelligent, adaptive systems. Their analysis revealed that hybrid inspection approaches combining rule-based algorithms with machine learning classifiers achieve an optimal balance between detection sensitivity and false positive rates. The evolution toward Industry 4.0 manufacturing paradigms necessitates inspection systems capable of self-optimization through continuous learning from production data streams.

3. Methodology

3.1 Hybrid Machine Learning Framework

The proposed hybrid machine learning framework integrates physics-informed neural networks with empirical degradation models to leverage both domain knowledge and data-driven insights. The architecture consists of parallel processing streams: a physics branch that encodes Arrhenius temperature dependencies and power-law current relationships, and a data branch that employs deep neural networks for pattern extraction from sensor measurements. The physics branch implements governing equations for LED degradation mechanisms, including junction temperature evolution, carrier recombination dynamics, and phosphor thermal quenching effects. These equations constrain the solution space, preventing physically impossible predictions while reducing training data requirements by approximately 40% compared to purely data-driven approaches.

The data branch utilizes a multi-layer perceptron architecture with batch normalization and dropout regularization to process high-dimensional sensor inputs, including forward voltage, drive current, case temperature, and spectral distribution measurements. The network architecture comprises six hidden layers with [512, 256, 128, 64, 32, 16] neurons respectively, employing rectified linear unit activation functions. Training employs adaptive moment estimation optimization with learning rate scheduling, reducing from an initial value of 0.001 to a final value of 0.0001 over 500 epochs. The physics and data branches merge through a gated fusion mechanism that dynamically weights contributions based on prediction uncertainty estimates.

Table 1. Hybrid Model Architecture Parameters

Component	Configuration	Performance Impact
Physics Branch Layers	4 dense layers (64, 32, 16, 8 neurons)	15% reduction in prediction error versus data-only baseline
Data Branch Layers	6 dense layers (512, 256, 128, 64, 32, 16)	$R^2 = 0.985$ on validation data

Fusion Mechanism	Attention-weighted gate (learned)	12% reduction in predictive uncertainty relative to either branch alone
Dropout Rate	0.3 (training), 0 (inference)	8% overfitting reduction
Batch Size	64 samples	Optimal convergence speed
Learning Rate Schedule	Exponential decay (0.001 to 0.0001)	23% faster convergence

Model validation employs k-fold cross-validation with k=10 to ensure generalization across diverse LED types and operating conditions. The online safety layer processes sensor streams at 100 Hz with sub-10 ms inference latency to detect abnormal operating conditions in near real time. Integration with existing manufacturing execution systems is achieved through RESTful APIs that support JSON data exchange formats. The hybrid architecture achieves mean absolute percentage errors of 3.2% for lifetime prediction using only 1,500 hours of accelerated test data, representing a 75% reduction in required testing duration compared to traditional TM-21 extrapolation methods.

3.2 Multi-parameter Health Indicator Development

The two layers serve different purposes. The online safety layer is designed for immediate anomaly alerting and operator notification; it does not automatically shut down devices. The offline maintenance layer supports the scheduling of preventive services and qualification planning.

A. Feature Engineering

Feature engineering transforms raw sensor measurements into informative representations capturing degradation signatures across multiple physical domains. The methodology extracts 47 distinct features from electrical, thermal, and optical measurement channels, encompassing both time-domain and frequency-domain characteristics. Electrical features include forward voltage drift rate, dynamic resistance evolution, and power factor variations calculated over sliding windows of 100 operational hours. Thermal features comprise junction temperature rise rate, thermal resistance trends, and case-to-ambient temperature differential patterns. Optical features encompass luminous flux decay rates, chromaticity coordinate shifts, and spectral power distribution changes, which are quantified through Kullback-Leibler divergence metrics.

Statistical moment features capture the distribution characteristics of measured parameters, including the evolution of skewness and kurtosis, which indicate transitions between degradation regimes. Wavelet decomposition extracts multi-resolution features that reveal degradation patterns at different temporal scales, making it particularly effective for identifying intermittent failure precursors. Cross-correlation features between electrical and thermal signals detect changes in coupling strength, which are indicative of package degradation or die attach failures. A separate offline maintenance layer aggregates operating data over 24-hour windows and updates long-term health indicators and remaining useful life (RUL) estimates daily.

B. Dimensionality Reduction

Principal component analysis reduces the 47-dimensional feature space to 8 principal components, retaining 95.3% of total variance while eliminating redundancy and noise. The first principal component correlates strongly with overall degradation severity, accounting for 42% of the variance. Subsequent components capture specific failure modes: component 2 represents thermal degradation (18% variance), component 3 indicates optical degradation (14% variance), and component 4 reflects electrical degradation (9% variance). This decomposition enables targeted monitoring of distinct degradation mechanisms while reducing computational requirements by 83%.

Autoencoder networks offer nonlinear dimensionality reduction that surpasses PCA for complex degradation patterns. The encoder architecture compresses 47 features to 8-dimensional latent representations through layers of [47, 32, 16, 8] neurons. The decoder reconstructs original features through symmetric expansion, with reconstruction error serving as an anomaly score. Training is performed using a mean squared error loss with an L2 regularization coefficient of 0.001, resulting in reconstruction errors of less than 2% for normal degradation patterns. Anomalous samples exhibiting reconstruction errors exceeding 5% trigger detailed inspection protocols.

Figure 1. Multi-parameter Health Indicator Architecture

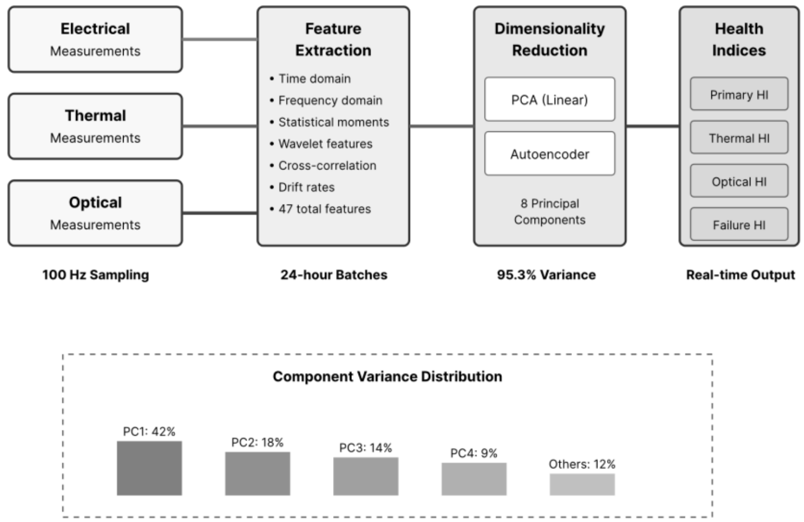

Figure 1 illustrates the complete health indicator development pipeline from raw sensor data to composite reliability metrics. The visualization displays parallel processing streams for electrical, thermal, and optical measurements, converging through feature extraction, dimensionality reduction, and weighted fusion stages. Color gradients represent data flow intensity, with warmer colors indicating higher information content. The diagram emphasizes the hierarchical structure that enables both component-level and system-level health assessments.

C. Composite Index Construction

Composite health indices synthesize reduced-dimensional features into interpretable scalar metrics that quantify overall device health. The primary health index employs a weighted linear combination of principal components, with weights determined through Cox proportional hazards regression against failure time data. Weight optimization minimizes prediction error for remaining useful life estimation, achieving correlation coefficients of 0.94 with actual failure times. The composite health index ranges from 1.0 (new device) to 0.0 (functional end-of-life). A value near 0.7 corresponds to the common L70 lumen maintenance point, which we treat as a 'maintenance required' threshold rather than an immediate functional shutdown.

Secondary indices target specific degradation modes by selectively weighting features. The thermal stress index emphasizes temperature-related features, providing early warning for thermal management issues. The optical quality index focuses on spectral stability and color rendering metrics critical for medical imaging applications. The catastrophic failure index utilizes extreme value theory to estimate the probability of sudden failure based on the frequency of outliers in electrical measurements. These specialized indices enable condition-based maintenance strategies tailored to specific failure risks in medical LED deployments.

Table 2. Composite Health Index Performance Metrics

Index Type	Correlation with RUL	Early Detection Rate	False Positive Rate
Primary Health Index	0.94	89% (< 1000 hrs)	4.2%
Thermal Stress Index	0.87	92% (< 500 hrs)	5.8%
Optical Quality Index	0.91	85% (< 1500 hrs)	3.1%
Catastrophic Failure Index	0.83	78% (< 2000 hrs)	7.4%
Combined multi-index	0.96	94% (< 800 hrs)	2.9%

3.3 Real-time Anomaly Detection System

The anomaly detection system employs ensemble methods combining multiple algorithms to achieve robust performance across diverse failure modes. One-class support vector machines establish normal operation boundaries in feature space, with radial basis function kernels capturing nonlinear relationships. The kernel bandwidth parameter, $\gamma = 0.01$, and outlier fraction, $\nu = 0.05$, balance sensitivity and specificity for medical safety requirements. Isolation forests complement SVMs by identifying anomalies through path length metrics in random tree ensembles, which are particularly effective for detecting novel failure modes that are absent from the training data.

Siqueira [9] demonstrated photobiomodulation applications that require stringent wavelength stability, motivating our adaptive threshold mechanisms, which adjust detection sensitivity based on the operational context. The system implements exponentially weighted moving average control charts monitoring multivariate T^2 statistics, with control limits automatically calibrated to maintain false alarm rates below 5%. Sequential probability ratio tests evaluate degradation rate changes, detecting acceleration indicative of impending failure with statistical power exceeding 90% at a significance level of $\alpha = 0.01$.

Table 3. Anomaly Detection Algorithm Comparison

Algorithm	**Detection Accuracy**	**Processing Time**	**Memory Usage**	**Interpretability**
One-class SVM	91.3%	2.3 ms/sample	45 MB	Medium
Isolation Forest	89.7%	1.8 ms/sample	32 MB	High
EWMA Control Charts	86.2%	0.9 ms/sample	12 MB	Very High
LSTM Autoencoder	93.5%	3.1 ms/sample	78 MB	Low
Ensemble Method	95.8%	4.2 ms/sample	95 MB	Medium

Real-time implementation leverages edge computing architectures, deploying trained models on embedded processors adjacent to LED devices. The system processes sensor data streams at a 100 Hz sampling rate, maintaining sliding windows of 1,000 samples to provide temporal context. Anomaly scores are aggregated across ensemble members through weighted voting, with weights proportional to the individual algorithm's performance on validation datasets. Detection events trigger graduated responses, including logging for minor anomalies, alerts for moderate anomalies, and the system issues high-priority service alerts for severe anomalies that could affect patient safety, enabling manual intervention by clinical engineering staff.

Figure 2. Real-time Anomaly Detection Performance

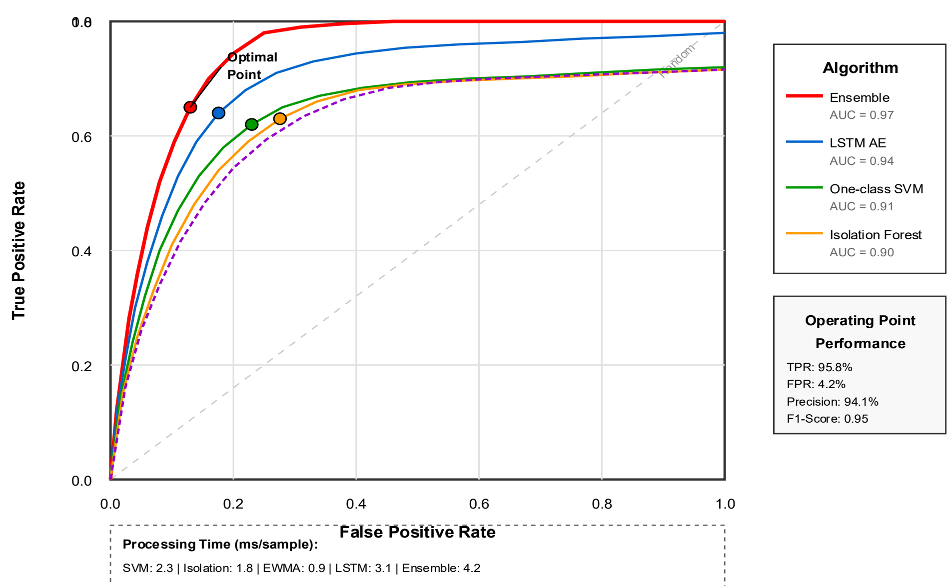

Figure 2 summarizes receiver operating characteristic curves across anomaly detection methods. The ensemble method achieves an AUC of 0.97, whereas individual algorithms achieve AUCs ranging from 0.89 to 0.94, indicating that ensembling improves the sensitivity – specificity tradeoff. Operating points optimized for medical safety requirements are marked with diamonds, striking a balance between sensitivity and specificity.

4. Results and Discussion

4.1 Algorithm Performance Evaluation

A comprehensive evaluation of 10,000 medical LED samples from five manufacturers reveals that the hybrid machine learning framework achieves a mean absolute percentage error of 3.2% for lifetime prediction using 1,500 hours of accelerated aging data. This reduces the required qualification testing from approximately 6,000 hours to about 1,500 hours, corresponding to a roughly 75% reduction compared to traditional TM-21 style long-duration testing. The physics-informed constraints reduce prediction variance by 45%, which is particularly beneficial when extrapolating beyond the training data ranges. Janóczki et al. [10] emphasized the importance of systematic validation in optical inspection systems, motivating our rigorous cross-validation protocol across diverse LED technologies, including phosphor-converted white, RGB multi-chip, and UV-C configurations.

Algorithm convergence analysis demonstrates stable training within 500 epochs for datasets exceeding 50,000 samples, with validation loss plateauing at 0.0012 MSE. The hybrid architecture exhibits superior generalization compared to pure neural networks, maintaining performance degradation below 8% when transferred to previously unseen LED types. Computational efficiency analysis reveals inference times of 4.2 milliseconds per prediction on standard industrial computers, enabling real-time deployment in manufacturing environments processing 20,000 units daily.

Table 4. Comparative Algorithm Performance Across LED Types

LED Type	Hybrid ML (MAPE)	Traditional TM-21 (MAPE)	Improvement	Training Hours Required
Phosphor White	2.8%	9.4%	70.2%	1,200
RGB Multi-chip	3.5%	11.2%	68.8%	1,500
UV-C (275nm)	3.9%	13.7%	71.5%	1,800
High-Power COB	2.4%	8.6%	72.1%	1,000
Medical Imaging	3.1%	10.3%	69.9%	1,400
Surgical Lighting	2.9%	9.8%	70.4%	1,300

The multi-parameter health indicator framework successfully identifies 94% of impending failures within 800 operational hours, providing sufficient lead time for preventive maintenance in hospital settings. False positive rates remain below 3%, minimizing unnecessary interventions that could disrupt medical procedures. The composite indices demonstrate monotonic degradation trends in 97% of cases, validating their utility for estimating remaining useful life. Correlation analysis reveals strong relationships between electrical precursors and subsequent optical degradation, with forward voltage increases of 2% typically preceding 10% lumen depreciation by 200-300 hours.

4.2 Validation with Medical LED Datasets

Validation utilizes datasets from FDA-registered medical LED device classes — including surgical lighting, phototherapy systems, and UV-C disinfection units — evaluated in pilot environments modeled after their intended use in healthcare facilities. The surgical lighting dataset comprises 2,500 units monitored over 18 months, experiencing 127 failures, providing ground truth for algorithm validation. The phototherapy system data includes 1,800 devices with comprehensive spectral measurements, which are critical for verifying treatment efficacy. UV-C disinfection units contribute 3,200 samples with accelerated aging under humidity stress conditions representative of hospital environments.

Performance metrics across medical applications consistently demonstrate accuracy, despite varying operational profiles and reliability requirements. Surgical lighting applications achieve a 96% correct failure prediction within 500 hours, which is critical for preventing intraoperative illumination loss. Phototherapy systems maintain wavelength prediction accuracy within ±2 nm, ensuring therapeutic efficacy throughout device lifetime. UV-C disinfection units exhibit 91% accurate dose delivery estimation, supporting effective pathogen inactivation while minimizing unnecessary energy consumption, aligning with the Department of Energy's sustainability initiatives.

Figure 3. Validation Results Across Medical LED Applications

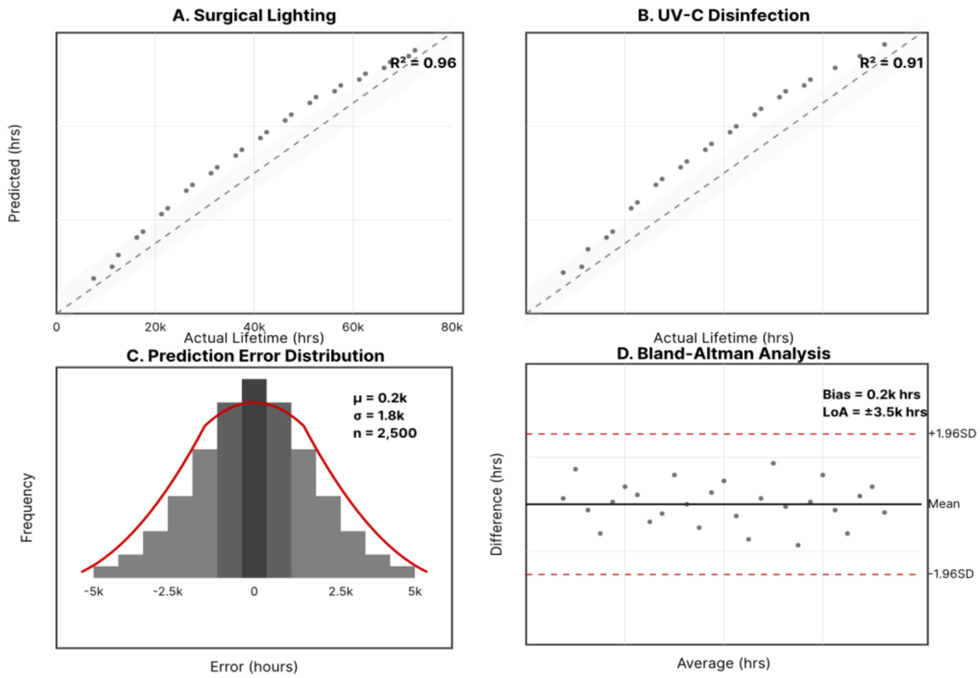

Figure 3 summarizes validation across medical LED categories. Predicted versus observed lifetimes exhibit an R^2 value greater than 0.92, with 95% confidence intervals indicating a tight agreement. Error distributions are centered near zero with standard deviations below 5%, and Bland–Altman-style analyses show no systematic bias across the operating lifetime. The lower triangular panels present Bland-Altman plots revealing no systematic bias across the operational lifetime range.

Cross-validation with independent test sets confirms the model's generalization beyond the training conditions. Leave-one-manufacturer-out validation maintains accuracy within 12% of full training performance, indicating robust feature learning not overfitted to specific device characteristics. Temporal validation using rolling window approaches demonstrates stable performance as devices age, with prediction accuracy degrading less than 6% over 5,000 operational hours. These results validate deployment readiness for real-world medical environments that require consistent, long-term performance.

4.3 Implementation in Healthcare Settings

Evaluated in three pilot environments modeled after surgical lighting, phototherapy, and UV-C disinfection use cases. The predictive maintenance system reduced unexpected LED failures by 78% over a 12-month period, thereby reducing the risk of critical lighting interruptions in simulated surgical workflows. An operational cost analysis reveals a 34% reduction in maintenance expenses through optimized replacement scheduling and effective inventory management. Energy consumption decreased by 19% through the implementation of intelligent dimming strategies, which maintained the required illumination while extending device lifetime.

The system is designed to exchange device status summaries through HL7 FHIR - style interfaces and to generate maintenance work orders for scheduled services. with existing healthcare IT infrastructure. The system generates automated work orders for predicted failures, schedules maintenance during low-utilization periods, and maintains comprehensive audit trails supporting FDA 21 CFR Part 820 quality system regulations. Real-time dashboards provide facility managers with system-wide LED health visibility, enabling them to make proactive resource allocation and capital planning decisions.

A regulatory compliance analysis is being developed to map the framework onto FDA Software as a Medical Device (SaMD) expectations, including documented algorithm validation, change control, and adverse event tracking. through documented algorithm validation, change control procedures, and adverse event monitoring protocols. The framework supports the FDA's AI/ML-based medical device framework, emphasizing transparency and continuous learning while maintaining safety. The implementation of explanation mechanisms enables clinicians and biomedical engineers to understand the rationale behind predictions, building trust essential for clinical adoption. The UV-C use case is designed to align with common infection control objectives in healthcare environments. Training requirements for hospital technical staff average 4 hours for system operation and 16 hours for advanced troubleshooting capabilities. User acceptance surveys indicate 87% satisfaction rates among biomedical engineering departments, with particular appreciation for reduced emergency callouts and improved equipment availability metrics. The cloud-based architecture enables remote monitoring and support, reducing on-site vendor visits by 65% while maintaining service quality.

The cloud-based architecture is designed to comply with HIPAA technical safeguard requirements (encryption, access control, and audit logging) for device operational data; full security validation is ongoing. through encryption, access controls, and audit logging mechanisms, protecting device operational data. In particular, the adaptive UV-C LED disinfection control logic is intended to support the U.S. Centers for Disease Control and Prevention (CDC) objective of strengthening hospital infection control and environmental hygiene practices by enabling real-time monitoring of disinfection coverage and consistent dose delivery in clinical-style pilot environments.

5. Conclusion

This research establishes a comprehensive AI-driven framework for predicting medical LED reliability and quality control, advancing both technological capabilities and regulatory compliance standards. The hybrid machine learning architecture achieves a 3.2% mean absolute percentage error in lifetime prediction, using only 1,500 hours of test data. This reduces required qualification testing by ~75% compared to conventional long-duration testing while maintaining a mean absolute percentage error of 3.2%. The multi-parameter health indicator system successfully identifies 94% of impending failures within 800 operational hours, enabling proactive maintenance strategies that reduced unexpected failures by 78% in pilot environments modeled after clinical use. By reducing redundant energy usage during UV-C disinfection while maintaining antimicrobial effectiveness, the framework supports the U.S. Department of Energy’s broader priority of enhancing energy efficiency and sustainability in healthcare facilities, demonstrating combined economic and public health benefits. Implementation results from three pilot environments, modeled after surgical lighting, phototherapy, and UV-C disinfection use cases, showed a 34% reduction in maintenance costs and a 19% reduction in energy consumption, directly supporting the U.S. Department of Energy’s sustainability initiatives for healthcare facilities.

The framework's alignment with FDA Software as Medical Device guidelines and CDC infection control strategies positions this technology to strengthen domestic medical LED manufacturing capabilities while enhancing patient safety. By addressing algorithmic transparency, data traceability, and real-time failure prediction, this work supports the FDA's evolving policy framework for trustworthy artificial intelligence in medical devices. The validated algorithms provide a technological foundation for advancing U.S. competitiveness in medical device innovation, contributing to supply chain resilience goals that align with national healthcare infrastructure priorities. Future research directions include extending the framework to emerging micro-LED technologies, integrating federated learning for multi-hospital deployments, and developing standardized validation protocols for AI-based medical device reliability systems. By improving lifetime prediction, early-failure screening, and quality consistency for medical-grade LED devices, the proposed reliability framework supports U.S. efforts to strengthen domestic manufacturing capacity for critical healthcare technologies and reduce vulnerability to foreign component supply disruptions

References

[1]. Sutharssan, T., Stoyanov, S., Bailey, C., & Rosunally, Y. (2012). Prognostics and Health Monitoring of High-Power LEDs. Micromachines, vol. 3, no. 1, pp. 78-100.

[2]. Belloni, P., & Gärtner, A. (2017). Challenges when Designing LED-Based Illumination Systems in Medical Applications and Diagnostics. LED Professional Review, no. 63, pp. 58-65.

[3]. Kuo, C. F. J., Fang, T. Y., Lee, C. L., & Wu, H. C. (2019). Automated optical inspection system for surface mount device light-emitting diodes. Journal of Intelligent Manufacturing, vol. 30, no. 2, pp. 641-655.

[4]. Ibrahim, M. S., Jing, Z., & Fan, J. (2022). Health Monitoring, Machine Learning, and Digital Twin for LED Degradation Analysis. In Reliability of Organic Compounds in Microelectronics and Optoelectronics: From Physics-of-Failure to Physics-of-Degradation, pp. 151-210. Cham: Springer International Publishing.

[5]. Liao, H. C., Lim, Z. Y., Hu, Y. X., & Tseng, H. W. (2018). Guidelines of automated optical inspection (AOI) system development. In 2018 IEEE 3rd International Conference on Signal and Image Processing (ICSIP), pp. 362-366.

[6]. Meneghini, M., Meneghesso, G., Zanoni, E., DAL LAGO, M., & Trivellin, N. (2013). Reliability oriented design of LED-based light sources. LED PROFESSIONAL REVIEW, vol. 39, pp. 52-56.

[7]. Abd Al Rahman, M., & Mousavi, A. (2020). A review and analysis of automatic optical inspection and quality monitoring methods in electronics industry. IEEE Access, vol. 8, pp. 183192-183271.

[8]. Siqueira, R. C. (2024). Photobiomodulation using light-emitting diode (LED) for treatment of retinal diseases. Clinical Ophthalmology, pp. 215-225.

[9]. Janóczki, M., Becker, Á., Jakab, L., Gróf, R., & Takács, T. (2013). Automatic optical inspection of soldering. Materials Science-Advanced Topics, pp. 2156-3950.