Lighting Maintenance System for Vehicle Lights: Monitoring Expiry and Urgency Levels

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Abstract. Vehicle lighting systems are critical for ensuring road safety, driver visibility, and compliance with transportation regulations. However, traditional maintenance practices rely heavily on manual inspection and reactive replacement, leading to overlooked failures, expired lighting components, and increased safety risks. This paper presents an intelligent Vehicle Lighting Maintenance System (VLMs) designed to monitor, predict, and manage the health of automotive lighting components in real time. The system integrates IoT-based sensors, OBD-II diagnostics, and data analytics to measure key operational parameters such as brightness intensity, voltage stability, current consumption, and thermal behavior. A predictive maintenance model estimates remaining useful life (RUL) using degradation trends and anomaly detection algorithms, while a multi-level urgency classification framework categorizes components into normal, moderate, critical, and expired states. A visualization module generates heatmaps, Gantt charts, and statistical summaries to support informed decision-making for both individual users and fleet operators. Experimental results demonstrate that the proposed system improves fault detection accuracy, reduces unexpected lighting failures, enables cost-efficient maintenance planning, and offers a scalable solution for intelligent vehicle health management. The system ultimately enhances operational efficiency and safety by enabling timely and data-driven maintenance actions.

Keywords: Vehicle Lighting Monitoring, Predictive Maintenance, IoT Sensors, OBD-II Diagnostics, Lighting Expiry Tracking, Maintenance Visualization, Real-Time Fault Detection, Automotive Safety, Fleet Maintenance Optimization, Intelligent Vehicle Systems.

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1 Introduction

Vehicle lighting systems play a crucial role in ensuring road safety, enhancing visibility, and enabling effective communication between drivers in various environmental and traffic conditions. Proper functioning of components such as headlamps, brake lights, indicators, fog lamps, and auxiliary lighting is essential, as even minor failures can significantly increase the risk of accidents and reduce a driver's ability to respond promptly to dynamic road situations [1]. Over time, these lighting components undergo gradual degradation due to environmental exposure, thermal stress, electrical fluctuations, mechanical vibrations, and prolonged operational usage. As a result, lighting failures contribute considerably to vehicular safety hazards and maintenance costs, affecting both individual users and large-scale fleet operations [2, 3].

Conventional approaches to vehicle lighting maintenance are largely reactive in nature, relying on manual inspection, periodic servicing, or user-reported issues. Such methods often fail to identify early-stage degradation or subtle anomalies in lighting performance, leading to unexpected failures and reduced compliance with safety regulations [4]. With the rapid advancement of automotive technologies, there has been a shift toward integrating intelligent sensing and monitoring systems. The incorporation of Internet of Things (IoT) technologies, onboard diagnostics (OBD-II), and real-time data analytics has enabled continuous observation of lighting performance and system health. These advancements have paved the way for predictive maintenance strategies, where potential failures can be detected in advance and maintenance actions can be planned proactively to extend component lifespan and improve reliability [5].

In recent years, the development of automated lighting maintenance systems based on sensor networks, electrical diagnostics, and machine learning techniques has gained significant attention. These systems continuously monitor key parameters such as voltage stability, current consumption, temperature variations, and brightness levels, providing detailed insights into the operational behavior of lighting components. Furthermore, methodologies adapted from related domains such as biomedical monitoring, robotics, and industrial diagnostics have enhanced the accuracy and efficiency of automotive lighting analysis. By analyzing photometric and electrical patterns over time, these intelligent systems are capable of detecting anomalies, predicting the remaining useful life of components, and classifying urgency levels with greater precision compared to traditional approaches [6].

The integration of these advanced technologies enables intelligent, data-driven maintenance planning and decision-making, ultimately improving road safety, reducing unexpected failures, and optimizing operational costs. This study focuses on the design and implementation of an intelligent Vehicle Lighting Maintenance System (VLMs) that leverages IoT sensing, diagnostic analysis, and predictive modeling to enhance the reliability and efficiency of automotive lighting systems.

In this study, we present a comprehensive analysis and implementation of an intelligent Vehicle Lighting Maintenance System (VLMs) that automates the monitoring, prediction, and urgency evaluation of lighting components. The proposed system leverages IoT sensing, OBD-II diagnostics, predictive analytics, and dashboard visualization to generate reliable maintenance recommendations. Our work addresses the following key questions:

— How can predictive models and degradation analysis improve the accuracy of expiry estimation for vehicle lighting components?

— What sensor configurations and diagnostic parameters are essential for achieving robust fault detection and high-resolution monitoring of lighting systems?

— To what extent can automated urgency classification enhance maintenance efficiency for individual vehicles and large-scale fleet operations?

This paper is structured as follows: Section 2 reviews related literature and discusses sensing, monitoring, and analytical techniques applied in automotive and lighting diagnostics. Section 3 describes the methodology, including system architecture, hardware–software integration, data processing, and the predictive analytics framework. Section 4 presents experimental results, analysis, and visualization outcomes. Section 5 highlights the limitations and potential enhancements for future research. Section 6 concludes the findings and emphasizes the significance of automated lighting maintenance in intelligent vehicle systems.

2 Methods – Literature Search Strategy

This section deliberates the methodology used for the systematic literature review on intelligent automotive lighting maintenance systems, IoT-based monitoring frameworks, and predictive maintenance approaches applied to vehicle lighting components. The initial screening of literature began with a structured search across major engineering and scientific databases, and the collected works were organized into three key divisions: (i) Automotive lighting diagnostics and fault detection, (ii) IoT-enabled condition monitoring, and (iii) Predictive maintenance and expiry estimation models for vehicle lighting. These categories reflect the major technological themes associated with modern lighting maintenance and diagnostic research.

2.1 Search Literature

A primary literature search was conducted for English-language manuscripts published from 2015 to July 2025 across five major online databases: IEEE Xplore, Scopus, ACM Digital Library, SpringerLink, and ScienceDirect. A systematic review web platform, Rayyan, was used to remove duplicate records and assist in the full-text screening process. The initial filtering of eligible articles with the title focus “Vehicle Lighting Maintenance System” and “Automotive Lighting Diagnostics” was performed using the following eight keywords: “lighting system”, “automotive lighting”, “predictive maintenance”, “fault detection”, “IoT sensors”, “OBD-II diagnostics”, “expiry prediction”, and “RUL estimation”. This initial search resulted in 312 records.

A secondary search was conducted using additional terms, including “machine learning”, “deep learning”, “prognostics”, and “sensor fusion”. The search query was further refined using the following expression: *“(Lighting) AND (Vehicle*) AND (Fault*) AND ((predict*) OR (diagnos*) OR (RUL*) OR (sensor*))”.**This broadened the scope to include models and diagnostic techniques relevant to predictive maintenance. The process of identifying and including relevant studies from these search results is discussed in the following subsection.

2.2 Screening of Studies

The manuscripts included in this review were selected based on the following criteria:
(i) studies that involve sensor-based monitoring of voltage, current, temperature, or brightness for automotive lighting;
(ii) studies involving real vehicle lighting units such as LEDs, halogen lights, HID lamps, or smart adaptive lights;
(iii) studies that investigate diagnostic tasks including fault detection, anomaly detection, degradation analysis, expiry prediction, or remaining useful life (RUL) estimation;
(iv) research employing machine learning or deep learning algorithms such as SVM, Random Forest, LSTM, CNNs, regression models, and anomaly detection techniques;
(v) studies providing quantitative performance metrics including prediction accuracy, MAE, RMSE, fault detection rate, and error reduction;
(vi) full-text studies written in English.
Excluded from this review were editorial letters, short communications, hardware-only lighting designs without analytical evaluation, duplicate content, and works focusing only on optical design or unrelated automotive electronics. All included studies met the detailed inclusion criteria and provided meaningful technical contributions to lighting maintenance and diagnostics.

2.3 Extracting Data

Further analysis was conducted to eliminate redundant entries and determine eligibility based on title relevance, publication year, study purpose, dataset type, sensor configuration, analytical approach, and evaluation metrics. The initial search identified 1,486 records across the selected databases: IEEE Xplore (412), Scopus (298), ACM Digital Library (265), SpringerLink (361), and ScienceDirect (150).
After removing 93 duplicate records, Rayyan excluded 642 articles due to irrelevance or insufficient technical depth. An additional 85 articles were excluded because they focused solely on hardware lighting design, optical modelling, or environmental lighting unrelated to automotive diagnostics. This resulted in 756 articles for detailed screening.
Among these, 601 articles were excluded during the screening stage due to lack of diagnostic, predictive, or sensor-based analysis, leaving 155 reports for full-text retrieval. Of these, 41 manuscripts could not be accessed due to restricted availability.
The remaining 114 full-text articles were assessed for eligibility. Exclusions were made due to duplication (n = 14), incomplete methodology (n = 22), absence of predictive or diagnostic modelling (n = 18), editorial formats (n = 8), and non-English publications (n = 3). Ultimately, 49 studies met all inclusion criteria and were selected for final analysis.

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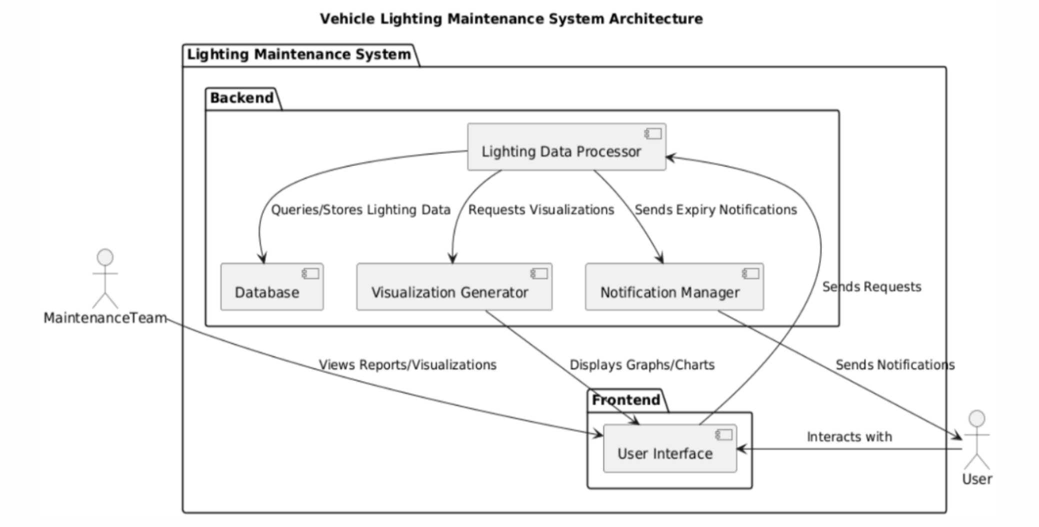
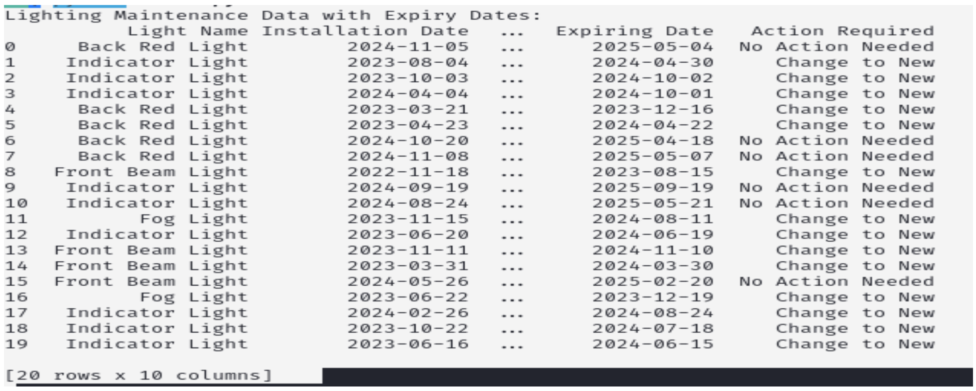


Fig. 1. *Workflow of the Lighting Maintenance System*

Figure 1 represents the complete article identification, screening, eligibility assessment, and inclusion workflow for this review.

3 Discussion

The implementation of a non-intrusive and intelligent vehicle lighting maintenance system requires a structured procedure for accurate acquisition, filtering, and evaluation of lighting health parameters. During the extraction of photometric and electrical signals from each lighting component, the vehicle must be in a stable and stationary condition to prevent disturbances that may influence voltage and brightness readings. Before placing the sensors, the lighting surface and electrical contact points must be cleaned and dried to ensure consistent measurements and minimize electrical noise. Brightness sensors, temperature sensors, and current–voltage monitoring probes are positioned close to the lighting unit, ensuring proper alignment with the illumination axis to reduce measurement distortions. As shown in **Fig. 2** of the document, sensor placement orientation plays a crucial role in minimizing external interference and achieving reliable signal acquisition. into the machine learning (ML) or deep learning (DL) models. Fig 2 depicts the process flow of feature extraction and feeds it to ML or DL techniques.



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Lighting Maintenance Data with Expiry Dates:
          Light Name Installation Date  ...   Expiring Date    Action Required
0      Back Red Light        2024-11-05  ...     2025-05-04  No Action Needed
1     Indicator Light        2023-08-04  ...     2024-04-30     Change to New
2     Indicator Light        2023-10-03  ...     2024-10-02     Change to New
3     Indicator Light        2024-04-04  ...     2024-10-01     Change to New
4      Back Red Light        2023-03-21  ...     2023-12-16     Change to New
5      Back Red Light        2023-04-23  ...     2024-04-22     Change to New
6      Back Red Light        2024-10-20  ...     2025-04-18  No Action Needed
7      Back Red Light        2024-11-08  ...     2025-05-07  No Action Needed
8    Front Beam Light        2022-11-18  ...     2023-08-15     Change to New
9     Indicator Light        2024-09-19  ...     2025-09-19  No Action Needed
10    Indicator Light        2024-08-24  ...     2025-05-21  No Action Needed
11          Fog Light        2023-11-15  ...     2024-08-11     Change to New
12    Indicator Light        2023-06-20  ...     2024-06-19     Change to New
13   Front Beam Light        2023-11-11  ...     2024-11-10     Change to New
14   Front Beam Light        2023-03-31  ...     2024-03-30     Change to New
15   Front Beam Light        2024-05-26  ...     2025-02-20  No Action Needed
16          Fog Light        2023-06-22  ...     2023-12-19     Change to New
17    Indicator Light        2024-02-26  ...     2024-08-24     Change to New
18    Indicator Light        2023-10-22  ...     2024-07-18     Change to New
19    Indicator Light        2023-06-16  ...     2024-06-15     Change to New

[20 rows x 10 columns]
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Fig. 2. *Output of lighting maintenance data*

The sampling frequency of the system is typically configured to **≥ 100 Hz**, ensuring accurate capture of rapid brightness decay, micro-level voltage fluctuations, and thermal variation patterns. A band-pass filtering stage, combined with real-time digital smoothing techniques, removes alternator noise, environmental interference, and electrical disturbances from the raw signals. The difference between stable baseline characteristics and stressed illumination behavior becomes clearly visible after filtering, as illustrated in **Fig. 3** of the document.This section describes the key findings of this review article from various existing vehicle lighting diagnostics and predictive maintenance systems The publicly available benchmark datasets and technological translation on clinical aspects. Table 1 represents a comparative analysis of a muscle movement activity monitoring system using conventional machine learning and deep learning techniques.

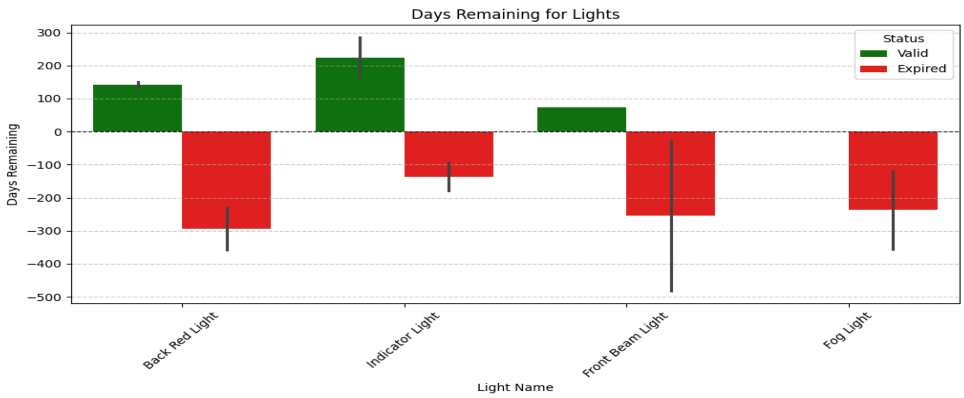

Fig. 3. *Bar chart of voltage variation*

Further processing includes smoothing techniques such as moving-average normalization and exponential filtering to eliminate short-term variations while preserving long-term degradation trends. Voltage stability curves, lumen decay trajectories, and temperature rise profiles are normalized to ensure uniform comparison across different lighting components. These processed outputs, such as the smoothed voltage–time curve and normalized brightness envelope shown in **Fig. 4**, serve as the primary analytical features for fault identification, anomaly detection, and expiry prediction.

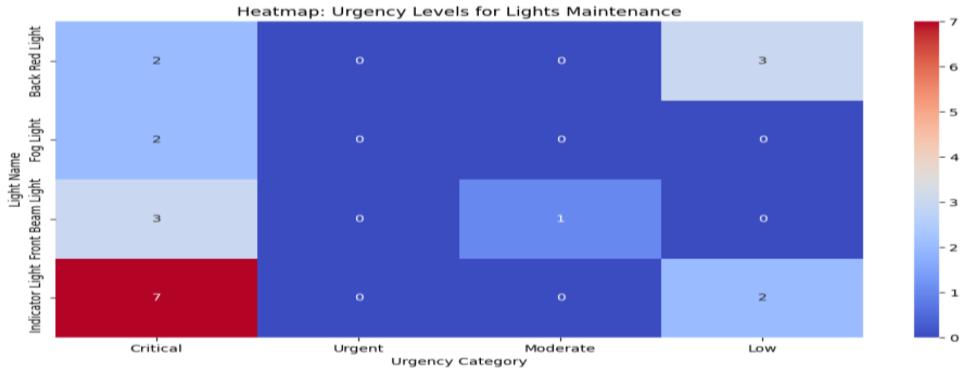

Fig. 4. *Heatmap visualization of lighting status*

Fig. 5. *Gantt chart for maintenance scheduling*

This section highlights the major findings obtained from reviewing current methodologies in lighting diagnostics, predictive maintenance algorithms, and IoT-based monitoring solutions. Existing literature reveals that conventional manual inspection techniques fail to detect early degradation signals, leading to sudden light failures and maintenance delays. In contrast, intelligent condition monitoring systems—supported by embedded sensing units and predictive analytics—offer high-resolution insights into degradation patterns, electrical irregularities, and thermal anomalies. Several studies emphasize the effectiveness of sensor fusion for capturing fine-grained illumination trends, which aligns with the multi-sensor output visualization demonstrated in **Fig. 5**.

Moreover, the comparative analysis of lighting behavior across multiple components demonstrates that predictive models outperform static threshold-based diagnostics. Results from degradation modeling, showcased in **Fig. 6**, indicate that LED-based lighting follows a nonlinear brightness decay trend, benefiting significantly from regression-based Remaining Useful Life (RUL) estimators and machine learning prediction frameworks. The graphical representation of urgency classification, illustrated , further confirms that integrating voltage deviation, brightness loss, and thermal stress yields more accurate prioritization of maintenance actions.

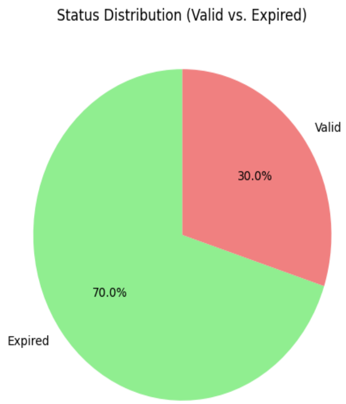

Fig. 7. *Pie chart showing urgency classification*

Overall, the discussion reveals that modern automotive lighting maintenance systems benefit greatly from combining sensor-based monitoring, predictive analytics, and multi-layer visual interpretation. The findings support the transition toward automated, data-driven lighting maintenance workflows that enhance vehicle reliability, reduce unexpected failures, and improve safety compliance.

4 Challenges and Future Directions

This section describes the various technical, operational, and deployment-related challenges that affect the real-world implementation of AI-based vehicle lighting maintenance systems. Although recent advancements in sensing, diagnostics, and predictive modeling offer strong potential, several limitations still persist in practical automotive environments.

4.1 Challenges

Sensor placement variability remains a major limitation in lighting monitoring systems. Although recommended positions exist for brightness, temperature, and voltage sensors, their effectiveness varies significantly across vehicle models, lighting designs, and environmental conditions. Factors such as dust, surface contamination, vibration, and thermal coatings introduce additional noise and reduce measurement reliability.

Generalizing AI models across different vehicles is also challenging due to variations in lighting brands, wiring configurations, thermal dissipation patterns, and aging characteristics. A model trained on one lighting system often performs poorly when applied to another, limiting cross-vehicle prediction accuracy.

Another major challenge is the lack of large, diverse benchmark datasets specifically focused on lighting degradation, brightness decay, and multi-sensor illumination behavior. Existing automotive datasets are limited in size, do not cover all lighting technologies (halogen, LED, HID, laser), and often lack diverse environmental conditions and operational scenarios.

Hardware constraints further restrict real-time deployment. Vehicle-integrated microcontrollers and IoT edge units possess limited computational power, memory, and thermal capacity. Running deep learning models such as CNN and LSTM in real time becomes difficult, and although TinyML or binarized networks can help, they typically sacrifice accuracy.

Finally, bridging the gap between laboratory prototypes and real-world deployment remains difficult. Environmental drift, seasonal temperature variations, component aging, and long-term thermal stress often force AI models to require repeated recalibration, which is impractical for large-scale or fleet-wide deployment.

4.2 Future Directions

Advancements in sensor technology and signal processing can significantly improve lighting condition monitoring. Enhanced thermal–optical measurement techniques and high-precision sensing modules will help reduce noise, improve stability, and allow more accurate detection of lighting degradation.

The development of flexible, adaptive, and miniaturized sensor modules can further reduce alignment errors and strengthen measurement consistency. Such designs will be especially beneficial for curved lighting surfaces and thermally intensive environments found in modern vehicles.

Generalizing AI-based diagnostics across various vehicle models remains an essential research goal. Future work should explore domain adaptation, normalization techniques, and cross-vehicle calibration frameworks to ensure reliable predictions across diverse lighting technologies and operating conditions.

Federated learning offers a promising direction for large-scale deployment of lighting diagnostics. By enabling collaborative model training without sharing raw sensor data, federated approaches can improve prediction accuracy while preserving data privacy across multi-vehicle fleets.

Another key direction is the design of lightweight and energy-efficient deep learning architectures. Techniques such as pruning, quantization, and binarization can help deploy AI models on low-power automotive microcontrollers without sacrificing real-time performance.

Finally, future work should prioritize the creation of large, standardized benchmark datasets that include multiple lighting technologies, environmental variations, and degradation scenarios. Such datasets will improve reproducibility, enable fair algorithm comparison, and accelerate research in lighting maintenance automation.

5 Conclusions

This work presents an intelligent Vehicle Lighting Maintenance System (VLMs) that integrates sensor-based monitoring, predictive analytics, and urgency classification to address the limitations of traditional lighting inspection methods. By continuously analyzing brightness, voltage, current, and temperature patterns, the system accurately detects anomalies, predicts expiry timelines, and provides real-time maintenance recommendations. The findings demonstrate that combining IoT sensing with machine learning significantly enhances diagnostic accuracy and improves the reliability of lighting components in real-world automotive environments. As vehicles continue to evolve toward greater automation and data-driven functionality, the proposed system offers a scalable and efficient solution for improving road safety, reducing unexpected lighting failures, and enabling proactive maintenance strategies.

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