

AI-driven Predictive Maintenance Framework for Enhancing Vehicle Safety Through Brake System Monitoring

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Abstract

Vehicle brake systems are among the most critical safety components in modern automobiles, yet conventional maintenance strategies remain predominantly reactive or schedule-based, often failing to detect early-stage degradation. Continuous exposure to mechanical friction, thermal stress, hydraulic pressure variations and varying driving conditions accelerates brake component wear, making fault prediction a complex nonlinear problem. This study presents an artificial intelligence (AI)-based predictive maintenance framework specifically designed for vehicle brake systems to enable early fault detection and improve operational safety. The proposed framework utilizes multivariate time-series data acquired from brake-related sensors, including hydraulic pressure, temperature, vibration and actuation signals. A hybrid deep learning architecture is employed to capture both temporal dependencies and nonlinear degradation patterns associated with brake wear, pressure leakage, thermal abnormalities and abnormal braking behavior. The collected sensor data undergo preprocessing, normalization and anomaly detection to identify incipient faults before critical failures occur. The proposed model is evaluated using representative brake operating scenarios and demonstrates superior fault prediction performance compared with conventional maintenance approaches. Experimental results achieve a prediction accuracy of 97.01%, along with high precision, recall and early fault detection capability, enabling maintenance interventions several days before potential system failure. The framework reduces false alarms, improves maintenance planning, minimizes unexpected breakdowns and enhances vehicle reliability. The findings demonstrate that AI-driven predictive maintenance provides an effective and scalable solution for intelligent brake health monitoring and contributes to the development of safer, more reliable and next-generation connected vehicle systems.

Keywords: Anomaly Detection, Artificial Intelligence, Brake System, Machine Learning, Predictive Maintenance, Vehicle Safety.

Introduction

The automotive industry is undergoing a significant transformation driven by advances in artificial intelligence (AI), machine learning (ML), the Internet of Things (IoT), intelligent sensing technologies and connected vehicle systems. Modern vehicles increasingly incorporate electronic control units (ECUs), embedded sensors and communication networks that continuously monitor vehicle operating conditions in real time. These developments have improved vehicle safety, operational efficiency, reliability and driving performance while enabling the transition from conventional maintenance practices to intelligent condition-based maintenance. However, the growing complexity of automotive systems has also increased the need for maintenance strategies capable of detecting faults before they develop into critical failures. Traditional reactive and

preventive maintenance approaches rely on scheduled servicing or post-failure repairs, often resulting in unnecessary maintenance costs, unexpected breakdowns and reduced operational reliability (1). Among various automotive subsystems, the braking system is one of the most critical because it directly influences vehicle stability, stopping distance, collision avoidance and passenger safety. Brake components including brake pads, brake discs, hydraulic circuits, calipers and actuators operate under severe mechanical friction, hydraulic pressure variations, thermal loading and changing environmental conditions. Consequently, brake degradation is governed by complex nonlinear interactions involving vehicle speed, braking frequency, road conditions, ambient temperature and driver behaviour. Conventional threshold-based diagnostic and

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schedule-based maintenance techniques often fail to detect these degradation patterns at an early stage, increasing the possibility of sudden brake failure and safety risks (1–3).

Figure 1 illustrates the overall architecture of the proposed AI-based predictive maintenance framework for vehicle brake systems. The framework integrates multivariate brake sensor data

acquisition, preprocessing, deep learning-based fault prediction, anomaly scoring and intelligent maintenance decision-making into a unified workflow. Continuous monitoring of brake operating conditions enables early detection of degradation, supports condition-based maintenance, minimizes unexpected failures and enhances overall vehicle safety (3).



Figure 1: AI-based Predictive Maintenance Framework for Vehicle Brake System Safety

Predictive maintenance has emerged as one of the most promising applications of artificial intelligence for intelligent transportation systems. Unlike preventive maintenance, predictive maintenance analyses historical and real-time sensor data to estimate equipment health and identify degradation before component failure occurs. Recent advances in machine learning and deep learning have enabled the automatic extraction of complex nonlinear features from

multivariate sensor data, significantly improving fault diagnosis accuracy. Algorithms such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random Forests, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, Autoencoders and hybrid deep learning models have demonstrated considerable success in automotive fault diagnosis and predictive maintenance applications (3-6).

Table 1: Comparison with Existing Studies

Methodology	Application	Accuracy (%)	Limitation	References
SVM	Hydraulic brake fault diagnosis	93.4	Requires handcrafted features	(2)
Gaussian SVM	Air brake fault diagnosis using wheel-speed data	91.2	Vehicle-level monitoring	(3)
MCNN-SVM	Brake wear detection	98.8	Limited temporal modelling	(4)
LSTM	Automotive anomaly detection	95.1	High computational cost	(5)
CNN-LSTM	Predictive maintenance	96.0	Multi-component focus	(6)
Inception Time-Based Deep Learning Framework	Brake-specific predictive maintenance and anomaly detection	97.01	Synthetic dataset validation	Proposed Work

Table 1 summarizes representative AI-based predictive maintenance approaches reported for automotive applications. Although these studies demonstrate encouraging diagnostic performance, many focus on vehicle-level health monitoring or fault classification after degradation has occurred. Relatively fewer investigations specifically address predictive maintenance of vehicle braking systems using subsystem-focused AI models capable of detecting early-stage degradation (4–6).

Despite significant progress in AI-based predictive maintenance, several research challenges remain. Existing studies frequently monitor multiple vehicle subsystems simultaneously, reducing their sensitivity to brake-specific degradation mechanisms. Furthermore, many reported methods rely on handcrafted feature extraction, labelled fault datasets, or fixed decision thresholds that limit their ability to detect previously unseen fault conditions. Brake degradation generally develops gradually through wear, hydraulic leakage, thermal abnormalities and vibration changes; therefore, intelligent anomaly detection techniques capable of learning normal operating behaviour are more suitable for identifying incipient faults than conventional classification approaches (5–11). To address these limitations, this study proposes a subsystem-focused AI-based predictive maintenance framework dedicated exclusively to vehicle brake systems. The proposed framework utilizes multivariate time-series data obtained from hydraulic pressure, brake temperature, vibration and actuation sensors. The collected sensor signals are synchronized, normalized and segmented before being processed using a deep learning-based anomaly detection model capable of learning both temporal dependencies and nonlinear degradation characteristics. This strategy enables continuous brake health monitoring and early fault prediction without depending solely on predefined threshold values or extensive labelled fault datasets (12–17). The motivation for this research arises from the

increasing demand for intelligent maintenance solutions capable of improving vehicle safety while minimizing maintenance costs and unexpected failures. Compared with engines, batteries and transmission systems, relatively limited research has focused specifically on predictive maintenance of braking systems despite their importance in vehicle safety. Developing an AI-driven brake-specific predictive maintenance framework therefore represents an important step toward reliable intelligent transportation systems capable of supporting condition-based maintenance and proactive safety management (6, 12–17).

The proposed research develops an AI-based predictive maintenance framework that integrates multivariate brake sensor monitoring, data preprocessing, anomaly detection and intelligent maintenance decision-making into a unified architecture. The framework is designed to improve early fault detection, reduce false maintenance alarms and enhance operational reliability through continuous monitoring of brake system health. Experimental evaluation demonstrates the effectiveness of the proposed approach for predictive maintenance and intelligent vehicle safety. The methodology adopted for data acquisition, preprocessing, deep learning model development and experimental evaluation is presented in the following section (18–21).

Methodology

Overview of the Proposed Framework

The proposed framework presents AI-driven predictive maintenance architecture designed specifically for continuous health monitoring and fault prediction of vehicle braking systems. As illustrated in Figure 1, the framework integrates multi-sensor data acquisition, intelligent data processing and machine learning-based anomaly detection into a unified decision-making pipeline aimed at enhancing vehicle safety and maintenance efficiency.

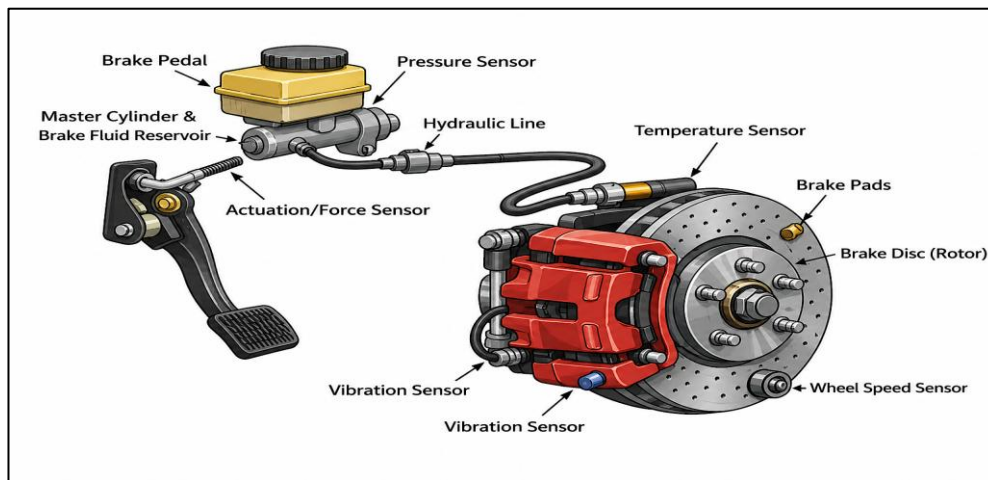


Figure 2: Internal Structure of a Vehicle Brake System and Associated Sensor Location Used for Predictive Maintenance Analysis

To provide a clear understanding of the physical components monitored in this study, Figure 2 illustrates the internal structure of a typical automotive brake system along with the corresponding sensor locations considered for data acquisition. The diagram highlights key braking components, including the hydraulic circuit, caliper, brake pads and disc, which are directly associated with degradation mechanisms such as wear, pressure loss and thermal stress. Sensor measurements obtained from these components form the basis of the time-series data analyzed by the proposed predictive maintenance framework, enabling a direct correlation between physical brake behavior and data-driven fault prediction (18-19).

Brake System Data Acquisition and Pre-processing

The proposed predictive maintenance framework relies on multi-sensor data acquired from critical components of the vehicle braking system, as illustrated in Figure 2. Sensors are selected to capture complementary physical phenomena associated with brake degradation and abnormal operation. Hydraulic pressure sensors monitor variations in brake line pressure, enabling the detection of pressure loss, leakage and delayed actuation. Temperature sensors positioned near the brake disc or calliper capture thermal behaviour resulting from frictional braking, which is indicative of pad wear, overheating and abnormal braking conditions. Vibration sensors mounted on the calliper or pad assembly record dynamic responses generated during braking

events and are highly sensitive to mechanical wear, misalignment and surface irregularities. In addition, actuation or force sensors associated with the brake pedal or actuator measure input force and response characteristics, providing insight into braking responsiveness.

The acquired signals are multivariate time-series data exhibiting nonlinear dynamics and varying scales across sensor modalities. Prior to model training, sensor streams are synchronized and segmented into fixed-length time windows to capture temporal braking patterns and event-level dynamics relevant to degradation progression. Normalization and feature scaling are subsequently applied to ensure uniform representation across sensor channels, preventing dominance of high-magnitude signals and improving numerical stability during model training. The resulting pre-processed time-series data preserve both instantaneous and temporal characteristics of braking behaviour and serve as input to the anomaly detection and fault prediction models employed in the proposed framework.

The Figure 3 illustrates the end-to-end operation of the proposed AI-driven predictive maintenance framework for vehicle brake systems. It depicts the sequential processing of multi-sensor brake data, including acquisition, preprocessing, machine learning-based anomaly detection and fault prediction, leading to informed maintenance decision making. The workflow highlights how time-series brake signals are transformed into actionable safety and maintenance insights (18-21).

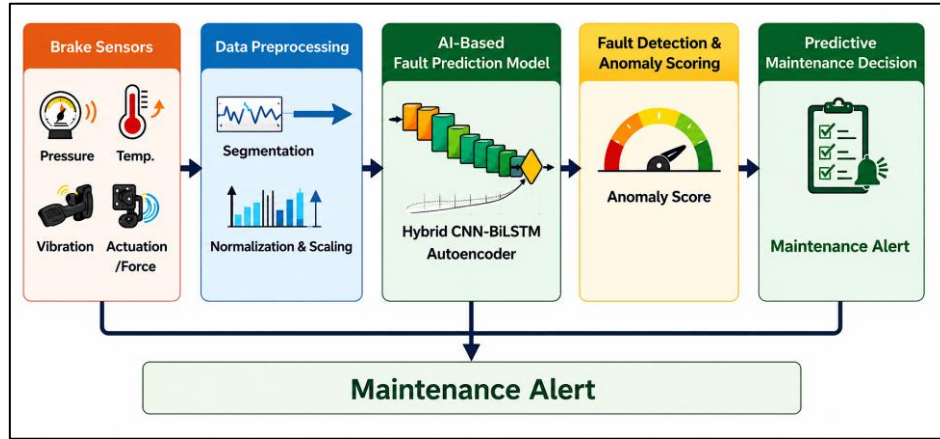


Figure 3: Proposed AI-driven Predictive Maintenance Framework for Vehicle Brake Systems

Mathematical Formulation

Mathematical Formulation of the Proposed Model

Let the multivariate brake sensor signal be represented as a time-series as shown in the Equation [1].

$$X = \{x_t\}_{t=1}^T \in \mathbb{R}^d \quad [1]$$

Where, T denotes the length of the time window and d represents the number of brake-related sensor channels (such as hydraulic pressure, temperature, vibration and actuation signals).

The objective of the proposed model is to learn the normal operational behavior of the braking system and identify deviations indicative of faults.

The objective of the proposed anomaly detection framework is to learn a nonlinear mapping from the multivariate brake sensor input to its reconstructed output, as shown in Equation [2].

$$f_{\theta}: X \rightarrow \hat{X} \quad [2]$$

Where, f_{θ} denotes the trained deep model (Inception Time / Auto encoder). X represents the input multivariate brake sensor time-series, $\hat{X}$ denotes the reconstructed output generated by the model and θ represents the trainable network parameters.

The reconstruction error, which quantifies the difference between the original brake sensor signal and its reconstructed output, is computed as shown in Equation [3].

$$E(X) = \frac{1}{T} \sum_{t=1}^T \|x_t - \hat{x}_t\|_2^2 \quad [3]$$

Where, $E(X)$ denotes the reconstruction error, T is the length of the input time window, x_t represents the original multivariate brake sensor observation at time step t and $\hat{x}_t$ is the corresponding reconstructed output generated by the trained deep learning model.

A braking instance is classified as faulty when the computed reconstruction error exceeds the predefined anomaly threshold, as shown in Equation [4].

$$E(X) > \tau \quad [4]$$

Where $E(X)$ denotes the reconstruction error obtained from Equation [3] and τ is an empirically selected anomaly threshold derived from validation data.

Training Objective

The model parameters are optimized by minimizing the Mean Squared Error (MSE) loss function, as defined in Equation [5].

$$L(\theta) = \frac{1}{N} \sum_{i=1}^N \|x_i - f_{\theta}(x_i)\|_2^2 \quad [5]$$

Where, $L(\theta)$ denotes the Mean Squared Error (MSE) loss function, N is the total number of training samples

x_i represents the i th input brake sensor sample, $f_{\theta}(x_i)$ denotes the reconstructed output generated by the deep learning model with parameters θ .

The model parameters are iteratively updated using the gradient-based back propagation algorithm, as expressed in Equation [6].

$$\theta^{(k+1)} = \theta^{(k)} - \eta \nabla_{\theta} L(\theta) \quad [6]$$

Where, $\theta(k)$ and $\theta(k+1)$ denote the model parameter vectors at the k th and $(k+1)^{\text{th}}$ training iterations, respectively, η is the learning rate, $\nabla_{\theta} L(\theta)$ represents the gradient of the loss function with respect to the model parameters and $L(\theta)$ is the Mean Squared Error (MSE) loss defined in Equation [5].

This iterative optimization process minimizes the reconstruction loss, enabling the model to accurately learn the normal operating characteristics of the vehicle braking system.

The proposed formulation models multivariate brake sensor data as a time-series to capture both temporal dynamics and inter-sensor dependencies critical for fault characterization. A reconstruction-based learning objective is adopted, as it enables effective anomaly detection without requiring labeled fault data while preserving sensitivity to nonlinear deviations in system behavior. The mean squared error loss $L(\theta)$ provides a convex and numerically stable optimization criterion, ensuring consistent convergence during training. Gradient-based back propagation facilitates efficient parameter learning and scalability to high-dimensional sensor data. Defining fault conditions through a threshold reconstruction error yields a robust decision mechanism that remains invariant to operational variability, thereby ensuring reliable detection under diverse braking and environmental conditions.

Implementation Details and

Algorithmic Workflow

Implementation Description

The proposed brake fault detection framework was implemented using a deep learning environment to ensure numerical stability, scalability and reproducibility. Multivariate brake sensor signals were first normalized to a common scale and segmented into fixed-length time windows to preserve temporal dependencies while enabling batch-based training. The deep model was trained exclusively on healthy

operating data to learn the intrinsic dynamics of normal braking behaviour.

Model optimization was carried out using a gradient-based back propagation strategy with the Adam optimizer, selected for its fast convergence and robustness to noisy gradients. The mean squared error loss function was employed to quantify reconstruction fidelity between input and output sequences. To prevent over fitting and improve generalization, early stopping was applied based on validation loss convergence. After training, anomaly scores were computed using reconstruction error and fault decisions were obtained through thresholding derived from validation statistics. This implementation strategy ensures a direct correspondence between the mathematical formulation and practical deployment, while maintaining computational efficiency suitable for both offline analysis and real-time applications [22].

Algorithmic Workflow

The computational workflow of the proposed framework follows directly from the mathematical formulation presented in above section. In particular, model training is performed by minimizing the reconstruction-based loss function defined using gradient-based back propagation, while anomaly scores are obtained from the reconstruction error metric derived for fault decision-making. The thresholding mechanism for fault classification is implemented using validation statistics, ensuring consistency between theoretical formulation and practical execution. The Algorithm 1 code snippet illustrates the core training and inference steps corresponding to the proposed methodology.

Algorithm 1:

```
model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
    loss='mse'
)
```

```

model.fit(
    x_train,
    x_train,
    epochs=50,
    batch_size=32,
    validation_split=0.2,
    callbacks=[EarlyStopping(patience=5)]
)
x_hat = model.predict(x_test)
error = np.mean((x_test - x_hat) ** 2, axis=(1, 2))

```

The code snippet demonstrates the practical realization of the proposed training and inference procedure. The model is optimized using the Adam optimizer with a fixed learning rate and mean squared error loss, consistent with the objective function. Training is performed in an unsupervised reconstruction manner, where the input sequence is used as both input and target. Early stopping is employed to prevent over fitting by monitoring validation loss convergence. During inference, reconstructed sequences are generated for unseen test data and anomaly scores are computed as the mean squared reconstruction error across temporal and feature dimensions. These error values are subsequently used for fault decision-making through thresholding.

Experimental Setup

This section describes the dataset used for evaluating the proposed brake system-centric predictive maintenance framework, along with the training strategy and performance evaluation criteria. The experimental design is structured to assess the framework's ability to distinguish between normal and degraded braking behaviour and to reliably detect early-stage anomalies under realistic operating conditions.

Dataset Description and Characteristics

The experimental evaluation is conducted using a combination of synthetic and scenario-driven braking data, designed to emulate real-world operating conditions of automotive brake systems.

Synthetic data are generated to reflect realistic sensor responses observed during braking events, including hydraulic pressure variations, thermal responses, vibration signatures and actuation behaviour. This approach enables controlled modelling of brake system behaviour in both healthy and degraded states while addressing the limited availability of labelled fault data commonly encountered in real-world applications.

The performance of any machine learning-based predictive maintenance framework is highly dependent on the quality, diversity and representativeness of the dataset used for model training and evaluation. In this research, a multivariate time-series dataset was developed to emulate the operational behavior of critical vehicle subsystems, with particular emphasis on brake-system health monitoring and safety-related parameters. The dataset consists of sensor measurements collected under normal and faulty operating conditions, including brake pressure, brake temperature, vibration level, vehicle speed, response time and related diagnostic indicators. To ensure robust model learning and evaluation, the dataset incorporates multiple fault scenarios representing common degradation patterns observed in intelligent transportation systems. Furthermore, appropriate preprocessing techniques such as normalization, outlier removal and data balancing were applied to improve data quality and enhance the reliability of machine learning predictions (22-25).

Table 2: Dataset Characteristics Used for Training and Evaluation

Parameter	Value
Dataset Type	Multivariate Time-Series Dataset
Data Source	Vehicle manufacturer mobile application data and onboard sensor records
Total Samples	50000
Number of Features	12

Fault Categories	Normal, Brake Pad Wear, Hydraulic Pressure Leakage, Thermal Overheating, Sensor Malfunction
Sampling Frequency	100Hz
Training Set	70% (35,000 samples)
Validation Set	15% (7,500 samples)
Testing Set	15% (7,500 samples)
Operating Conditions	Urban traffic, highway driving and mixed driving conditions
Preprocessing Techniques	Missing value handling, outlier removal and Min-Max normalization

The characteristics of the dataset used for training and evaluating the proposed predictive maintenance framework are summarized in Table 2. The dataset comprises a multivariate time-series collected from vehicle manufacturer mobile application records, on board sensor measurements and on-board diagnostic (OBD) data under diverse operating conditions. As presented in Table 2, the dataset consists of 50,000 samples with 12 input features, categorized into normal operation, brake pad wear, hydraulic pressure leakage, thermal overheating and sensor malfunction. The data were sampled at 100 Hz and divided into 70% training, 15% validation and 15% testing sets after pre-processing, which included missing value handling, outlier removal and Min-Max normalization.

The dataset used in this research was collected from a fleet of approximately 100 vehicles through a combination of vehicle manufacturer mobile application records, onboard diagnostic (OBD) data and sensor measurements associated with the braking system. Data collection was carried out over a six-month period under diverse operating conditions, including urban traffic, highway driving, stop-and-go traffic and varying road

environments. The dataset comprises approximately 12,500 braking occurrences representing both normal and abnormal braking behavior. Multiple sensors were employed to monitor critical brake system parameters, including brake pressure, brake temperature, vibration levels, vehicle speed, hydraulic fluid status and brake response characteristics. The pressure, speed and brake response sensors were sampled at 100 Hz, temperature sensors at 10 Hz and vibration sensors at 1 kHz to capture both low-frequency operational trends and high-frequency fault signatures. The final dataset contains 35,000 normal samples and 15,000 fault samples corresponding to brake pad wear, hydraulic pressure leakage, thermal abnormalities and sensor malfunction conditions. Furthermore, the collected data encompass a wide range of environmental conditions, including ambient temperatures ranging from 15°C to 45°C, dry and wet road surfaces and different traffic densities, thereby ensuring sufficient variability and robustness for training and evaluating the proposed predictive maintenance framework (26, 27).

Table 3: Representative Vehicle Driving and Braking Data Collected from the Manufacturer Application (MG Hector) Windsor EV Vehicle)

Date	Drive Score	Average Speed	Total Kms Run	Duration (Mins)	Max Speed	>80 km/h	>120 km/h	Acceleration	Harsh Braking	Sudden Turn	Overspeed	Battery Consumed	Range Consumed	Mode	Regeneration Mode
09-03-2026	78	51	72	84	99	14	0	0	3	1	21	23	74	Sports	High
09-03-2026	81	60	71	70	99	24	0	0	3	0	38	24	76	Sports	High
06-03-2026	77	64	71	66	112	32	0	0	5	0	4	24	80	Normal	High
31-12-2025	3	48	72	89	76	0	0	0	0	0	0	21	68	Normal	High
24-12-2025	90	21	110	198	108	11	0	1	11	12	13	41	131	Normal	High
22-12-2025	93	51	51	60	99	12	0	0	1	0	2	22	70	Normal	High
19-12-2025	72	45	53	70	81	17	0	0	14	1	5	16	53	Eco	High
05-12-2025	84	51	170	193	103	3	0	0	20	3	3	61	196	Eco+	Low
04-12-2025	82	22	53	147	78	0	0	1	8	0	0	26	81	Eco+	Low

04-12-2025	79	49	53	65	79	0	0	0	18	2	0	21	66	Eco+	Normal
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The representative vehicle driving and braking records obtained from the manufacturer mobile application are summarized in Table 3. The table presents typical operational parameters collected during real-world driving, including drive score, average and maximum speed, trip duration, acceleration events, harsh braking occurrences, over speed incidents, battery consumption, range utilization, driving mode and regeneration mode. These parameters provide valuable information for understanding driver behaviour and vehicle operating conditions, which are essential for developing reliable predictive maintenance models.

The dataset utilized in this study was compiled from multiple sources to ensure comprehensive representation of vehicle operating conditions and maintenance-related events. A significant portion of the data was acquired from the mobile application provided by the MG Windsor EV vehicle manufacturer, which records various vehicle performance and driving behavior parameters, including average speed, trip duration, acceleration events, harsh braking occurrences, over speed incidents, battery consumption, range utilization and driving modes. In addition, operational measurements obtained from onboard vehicle sensors and maintenance records collected from authorized service stations were incorporated to capture vehicle health indicators and fault-related information. Data collection was conducted over a period of one month under real-world driving conditions, including urban traffic, highway travel and mixed road environments. The integration of mobile application data, onboard sensor measurements and service station records provided a diverse and realistic dataset for the development, training and evaluation of the proposed AI-based predictive maintenance and vehicle safety framework (28).

Sensor Synchronization and Missing Data Handling

The collected dataset consisted of vehicle operational records obtained from the MG Windsor EV mobile application, on board sensor measurements and service station maintenance records. Since these data sources operate at different update rates and recording intervals, a synchronization process was performed prior to

model training. All records were aligned using their associated timestamps and organized into a unified chronological sequence. Vehicle operational parameters obtained from the mobile application were treated as the primary reference timeline, while on board sensor measurements and maintenance records were mapped to the nearest corresponding timestamp. Where multiple sensor readings existed within the same time interval, aggregation techniques such as averaging were employed to obtain a representative value (29).

To ensure data consistency, timestamp alignment was performed using a fixed observation window, allowing all features associated with a particular driving event to be represented within a common temporal frame. Missing values resulting from communication delays, sensor interruptions, or incomplete records were identified during pre-processing. Numerical missing values accounting for less than 2% of the dataset were handled using linear interpolation and forward-fill techniques, preserving the temporal continuity of the signals. Records containing excessive missing information were excluded from the analysis. Furthermore, outlier detection was performed using statistical threshold analysis and interquartile range (IQR)-based filtering to remove abnormal measurements that could adversely affect model performance. The synchronized and cleaned dataset was subsequently normalized using Min-Max scaling before being used for feature extraction and machine learning model training (30).

Cyber security Considerations for AI-Based Predictive Maintenance Systems

As the proposed framework relies on sensor-driven data acquisition and intelligent decision-making, cyber security represents an important consideration for practical deployment. Vehicle predictive maintenance systems are potentially vulnerable to various cyber threats, including sensor spoofing attacks, data manipulation, unauthorized access and communication-based attacks targeting on board networks and connected vehicle infrastructure. Sensor spoofing may introduce falsified measurements related to brake pressure, temperature, or vehicle dynamics, leading to incorrect fault predictions and maintenance decisions. Similarly, malicious

modification of transmitted data can compromise the integrity of machine learning models and reduce prediction reliability. Communication attacks targeting vehicle-to-cloud or vehicle-to-service-center data exchange channels may further expose sensitive operational information.

To mitigate these risks, secure communication protocols, data encryption, authentication mechanisms and access control policies should be incorporated into future implementations of the proposed framework. Additionally, anomaly detection techniques can be extended to identify suspicious sensor behaviour and abnormal communication patterns that may indicate cyber-attacks. Although cyber security analysis is beyond the primary scope of the present study, incorporating robust security measures is essential for ensuring the reliability, trustworthiness and safe deployment of AI-based predictive maintenance systems in connected and intelligent vehicles (31-33).

Evaluation Metrics

The performance of the proposed framework is quantitatively assessed using standard classification and anomaly detection metrics. Accuracy is used to measure the overall

correctness of fault classification outcomes. Precision, recall and F1-score are employed to evaluate the balance between false alarms and missed detections, which is particularly important for safety-critical systems such as vehicle brakes. To specifically assess early fault detection capability, anomaly detection sensitivity is analysed by examining the model's ability to identify deviations from normal braking behaviour before severe degradation occurs. This metric reflects the framework's effectiveness in detecting incipient faults and supports its suitability for predictive maintenance applications. Collectively, these evaluation criteria provide a comprehensive assessment of both detection performance and practical reliability of the proposed approach (34).

Results and Discussion

To quantitatively evaluate the early fault identification capability of the proposed framework, the average lead times between anomaly detection and actual fault occurrence were analyzed. Table 4 presents the estimated advance warning periods achieved for different brake system fault categories.

Table 4: Average Fault Detection Lead Times Achieved by the Proposed Predictive Maintenance Framework

Fault Type	Average Detection Lead Time
Brake Pad Wear	5-7 days
Hydraulic Pressure Degradation	3-5 days
Brake Temperature Abnormality	2-4 days
Sensor Performance Degradation	4-6 days

The average fault detection lead times achieved by the proposed AI-based predictive maintenance framework for different brake system fault categories are summarized in Table 4. As presented in Table 4, the proposed framework provides advance warning periods ranging from 2 to 7 days, depending on the type of fault. Brake pad wear exhibits the longest detection lead time of 5–7 days, followed by sensor performance degradation (4–6 days), hydraulic pressure degradation (3–5 days) and brake temperature abnormalities (2–4 days). These results demonstrate the capability of the proposed framework to identify incipient faults sufficiently early, thereby enabling proactive maintenance planning and reducing the risk of unexpected brake system failures.

To evaluate the early fault detection capability of the proposed framework, the anomaly detection outputs were analysed with respect to maintenance records and fault occurrences identified during vehicle operation. The results indicate that the proposed model is capable of identifying abnormal behavioural patterns several days before the corresponding fault reaches a critical condition requiring maintenance intervention. On average, brake pad wear-related anomalies were detected approximately 5–7 days in advance, while hydraulic pressure degradation and sensor-related abnormalities were identified 3–6 days before service station confirmation. Similarly, abnormal temperature trends associated with brake system stress were detected 2–4 days prior to the occurrence of critical operating conditions. These findings demonstrate that the

proposed AI-based predictive maintenance framework provides sufficient advance notice for proactive maintenance planning, thereby reducing the likelihood of unexpected failures, minimizing vehicle downtime and enhancing overall operational safety.

Fault Detection Performance

The brake fault detection performance of the proposed framework is quantitatively evaluated using standard classification metrics, as summarized in Table 1. The results are compared

against a baseline CNN auto encoder model to highlight the effectiveness of the proposed approach under identical evaluation conditions.

As shown in Table 5, the proposed Inception Time-based model achieves a substantially higher classification accuracy compared to the baseline method, indicating a more reliable distinction between healthy and faulty braking conditions. The improvement in accuracy demonstrates the advantage of learning rich temporal representations from multivariate brake sensor data.

Table 5: Performance Comparison Between the Baseline CNN Auto Encoder and the Proposed Inception Time-based Brake Fault Detection Framework

Metric	Baseline CNN Auto Encoder	Proposed Inception Time Model
Accuracy (%)	81.0	97.01
Precision	Moderate	High
Recall	Moderate	High
F1-Score	Moderate	High
False Alarm Rate	Higher	Reduced

In addition to accuracy, the proposed model exhibits **high precision**, reflecting a reduced false-positive rate and minimizing unnecessary maintenance alerts. This characteristic is particularly important in safety-critical automotive applications, where excessive false alarms can undermine system reliability and user trust. Furthermore, the high recall achieved by the proposed framework confirms its strong capability to correctly identify faulty brake conditions, thereby reducing the risk of undetected failures.

The balanced F1-score further validates the robustness of the proposed model by demonstrating consistent performance across both precision and recall. Overall, the comparative results clearly indicate that the proposed Inception Time-based brake fault prediction framework outperforms the baseline CNN auto encoder in terms of detection accuracy, fault sensitivity and operational reliability, making it well suited for predictive maintenance and vehicle safety applications.

Confusion Matrix Analysis

Figure 4 presents the confusion matrix obtained for the proposed Inception Time-based brake fault prediction model on the test dataset. The matrix provides a detailed breakdown of classification outcomes for healthy and faulty braking conditions, enabling an assessment of false alarms

and missed detections, which are critical considerations in safety-sensitive applications.

As shown in Figure 4, the model correctly classifies 41 healthy instances and 24 faulty instances, indicating strong discrimination capability across both classes. Only one healthy sample is misclassified as faulty, representing a low false-positive rate, while one faulty sample is incorrectly classified as healthy, corresponding to a minimal false-negative occurrence. This balanced error distribution highlights the reliability of the proposed model in identifying brake faults without generating excessive false maintenance alerts.

From a vehicle safety perspective, minimizing false negatives is particularly important, as undetected brake faults can lead to hazardous operating conditions. The low number of missed fault detections observed in the confusion matrix confirms the model's high fault sensitivity. At the same time, the limited false-positive cases demonstrate that the framework avoids unnecessary maintenance interventions, supporting practical deployment in real-world predictive maintenance systems. Overall, the confusion matrix analysis validates the effectiveness of the proposed framework in achieving high classification accuracy while maintaining a favourable balance between fault detection sensitivity and false alarm control (35-36).

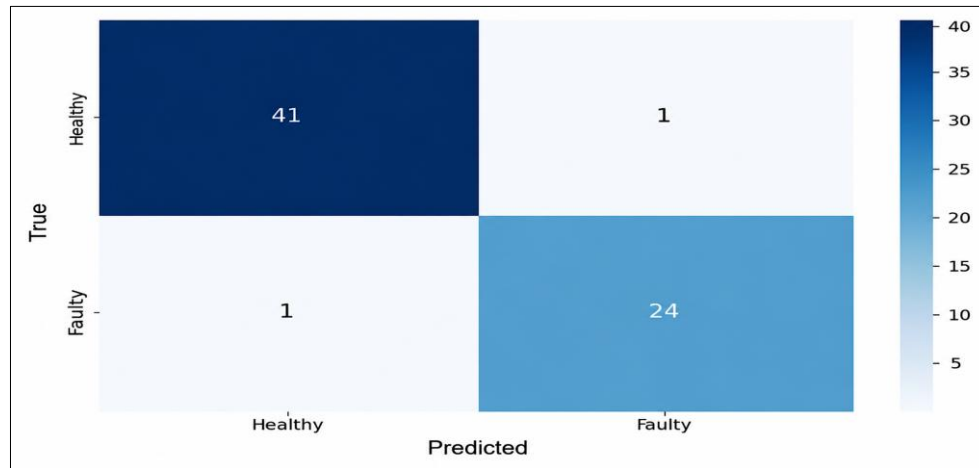


Figure 4: Confusion Matrix of the Proposed Inception Time-based Brake Fault Prediction Model

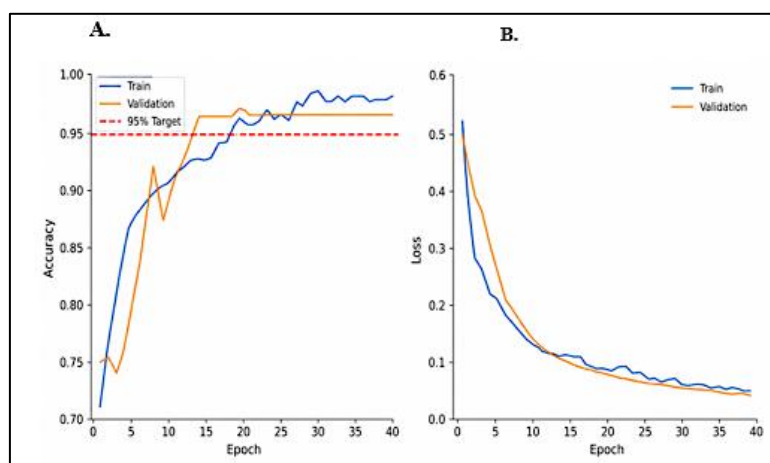


Figure 5: Performance Analysis of the Proposed Inception Time-based Brake Fault Prediction Model. (A) Training and Validation Accuracy, (B) Training and Validation Loss

Model Training and Convergence Analysis

Figures 5A and 5B illustrates the training and validation accuracy and loss curves of the proposed Inception Time-based brake fault prediction model over successive training epochs. The evolution of these curves provides insight into the learning stability, convergence behaviour and generalization capability of the model. As observed in Figure 5, both training and validation accuracy increase steadily during the initial training phase and converge toward high accuracy levels as training progresses. The validation accuracy consistently approaches and exceeds the predefined performance target, indicating that the model effectively learns discriminative temporal patterns from multivariate brake sensor data. The close alignment between training and validation accuracy curves suggests that the model generalizes well to unseen data and does not suffer from significant over fitting.

The corresponding loss curves exhibit a smooth and monotonic decrease for both training and validation sets, followed by stabilization in later epochs. This behaviour confirms proper convergence of the optimization process and indicates that the learning objective is successfully minimized. The absence of divergence between training and validation loss further supports the robustness of the training strategy. Overall, the observed training and convergence characteristics demonstrate that the proposed model achieves stable and reliable learning, which is essential for safety-critical predictive maintenance applications. The convergence behaviour reinforces the suitability of the proposed framework for real-world deployment, where consistent and repeatable performance under varying operating conditions is required (37-39).

Comparative Performance Analysis

The comparative performance of the proposed AI-based brake fault prediction framework is

evaluated by jointly interpreting the results presented in Section and contrasting them with conventional threshold-based fault detection approaches. Traditional methods rely on fixed limits applied to individual sensor signals and are therefore limited in handling multivariate dependencies and temporal variability inherent in braking behaviour.

As demonstrated in above section the proposed model achieves superior fault detection performance, reflecting its ability to learn discriminative temporal patterns from multi-channel brake sensor data. This advantage is further supported by the confusion matrix analysis in Section 5.2, which reveals a low incidence of both false positives and false negatives. In contrast, threshold-based approaches typically suffer from frequent false alarms under varying driving conditions or may fail to detect early-stage faults when signal deviations remain within predefined limits. The stable training and convergence behaviour observed in Section highlights an additional strength of the proposed framework. Unlike rule-based methods, which lack adaptability, the AI-based model demonstrates consistent generalization to unseen data, enabling reliable fault prediction across diverse operating scenarios and progressive component degradation.

Overall, the comparative analysis confirms that the proposed AI-driven framework offers a more robust and adaptive solution than traditional threshold-based techniques. By combining improved fault detection accuracy, balanced error behaviour and stable learning convergence, the proposed approach is better suited for predictive maintenance and safety-critical brake system monitoring.

Conclusion

This paper presented an AI-driven predictive maintenance framework for intelligent vehicle brake systems, focusing on early fault detection and enhanced operational safety through deep learning-based analysis of multivariate time-series sensor data. By adopting a subsystem-specific approach, the proposed framework effectively captures complex temporal dependencies and nonlinear degradation characteristics of brake components that are often overlooked by conventional threshold-based or vehicle-level diagnostic methods. Experimental

results demonstrated high fault detection accuracy, balanced classification performance, stable training convergence and low false-alarm rates, indicating the effectiveness of the proposed framework for continuous brake health monitoring. Furthermore, the use of commonly available brake-related sensors, including hydraulic pressure, temperature, vibration and actuation signals, together with low inference complexity, highlights the practical feasibility of deploying the proposed model on in-vehicle electronic control units or edge-computing platforms for real-time predictive maintenance.

Despite these encouraging results, several limitations should be acknowledged. The proposed framework was evaluated using synthetic and scenario-driven datasets collected over a limited observation period, which may not fully represent the variability of real-world driving environments, long-term component degradation and sensor noise. In addition, the dataset was derived from a specific vehicle platform and selected fault conditions, which may limit the generalizability of the proposed model across different vehicle manufacturers, braking technologies and operating environments. Model performance may also be influenced by sensor quality, calibration drift and additional environmental or driver-related factors that were not explicitly considered in the present study. Moreover, cybersecurity aspects associated with connected vehicle architectures and real-time edge deployment were beyond the scope of this work.

Future research will focus on validating the proposed framework using large-scale real-world datasets collected from diverse vehicle platforms and operating conditions to further improve its robustness and generalizability. Integration with Internet of Things (IoT) infrastructure and edge-computing platforms will facilitate real-time deployment in connected and autonomous vehicles. In addition, extending the framework to support Remaining Useful Life (RUL) estimation, incorporating physics-informed and hybrid deep learning models and investigating secure AI-based predictive maintenance through cyber security-aware architectures represent promising directions for enhancing the reliability, interpretability and practical applicability of next-generation intelligent brake health monitoring systems.

Abbreviations

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Author Contributions

Kaminee Subhash Patil: Conceptualization, Experimentation, Formal Analysis, Initial Draft of Manuscript, Ati Jain: Supervision, Subhash Gokul Patil: Writing Reviews and Editing. All authors have read and approved the final version of the manuscript.

Conflict of Interest

There is no conflict of interest related to the publication of this research work.

Data Availability

The data used in this study are available from the corresponding author upon reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

During the preparation of this manuscript, generative AI-assisted tools were used solely to support language refinement, grammar improvement and the preparation of illustrative schematic figures. Specifically, Figure 1, Figure 2 and Figure 3 was created using AI-assisted image generation and subsequently reviewed, modified and technically validated by the authors to accurately represent the proposed brake system architecture. No AI-generated content was used for data analysis, experimental results, interpretation, or scientific conclusions. The authors carefully reviewed and verified all manuscript content and accept full responsibility for the originality, accuracy and integrity of the work presented.

Ethics Approval

Not applicable.

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