Hybrid ML-Weibull Predictive Maintenance System for Dynamic Tire Remaining Useful Life Estimation

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Abstract

Tire failure is a major contributor to road fatalities, accounting for 3% to 15% of fatal accidents globally. Conventional Tire Pressure Monitoring Systems (TPMS) are limited by their reactive nature, as they only alert drivers to under-inflation after it occurs and cannot predict gradual wear or Remaining Useful Life (RUL). This research proposes a hybrid Predictive Maintenance framework that integrates Machine Learning with the Weibull reliability distribution to provide dynamic RUL estimations. Unlike existing simulation-centric or static models, the developed system utilizes an edge-cloud architecture centered on an ESP32-S3 gateway to capture telemetry from TPMS, OBD-II, and GPS modules. By treating the Weibull scale parameter (λ) as a dynamic covariate influenced by operational stressors such as engine load, vehicle speed, pressure, and temperature, the model continuously adapts to the tire's degradation trajectory. Empirical results from field testing demonstrate that the covariate-driven approach significantly outperforms static baselines. The LightGBM regressor achieved the highest precision with a near-negligible MAPE of 0.0025 and a MASE of 0.2168. Specialized reliability metrics, including MQWE, further confirm the model's ability to minimize high-risk outliers, while an analysis of pessimistic error profiles ensures that maintenance is prompted before catastrophic failure. This study provides a scalable, real-time solution for in-vehicle Prognostics and Health Management (PHM), offering a robust pathway to reducing tire-related road casualties.

Keywords Predictive Maintenance, RUL, Tire Health Monitoring, Machine Learning, Weibull Distribution, Telemetry.

1 Introduction

Tire failure contributes significantly to road fatalities, with studies reporting it as a factor in 3-15% of fatal accidents depending on the region, such as 15.2% in Ghana. NHTSA data indicates tire related crashes cause hundreds of deaths annually in the US, including over 500 fatalities linked to tire defects. For instance, tire blowouts and tread separations have been implicated in high profile crashes involving vehicles like SUVs and trucks [1].

Conventional TPMS are primarily reactive, alerting to low pressure after it occurs but failing to predict gradual wear or RUL. They detect underinflation but cannot foresee tire degradation from wear, temperature, or load, limiting proactive maintenance. Scientific reviews emphasize the need for ML based predictive models beyond TPMS for tire health prognostics [2].

While the Honda RI work (Nguyen et al., 2019) pioneers physics-based damage models (e.g., Paris-Erdogan for springs, wear volume for tires/brakes) combined with data-driven ML (polynomial, RF, DT) and fleet simulations via CarMaker to predict tire damage percentages and fleet-level RUL, it relies on aggregated historical/simulated data without real-time telemetry integration from live sensors like TPMS or OBD-II. This static, simulation-centric approach yields accurate damage histograms (e.g., R^2>95% for polynomials) but neglects dynamic environmental stressors (e.g., pressure/temperature fluctuations) and probabilistic reliability modeling, limiting applicability to proactive, in-vehicle PHM where covariates evolve continuously [3].

Using FusionNet introduces a hybrid deep learning framework that fuses structured sensor data with image analysis (e.g., ResNet or EfficientNet for tread visuals and XGBoost or LightGBM for telemetry) to predict tire lifespan, it primarily emphasizes static post-processing classification of wear states rather than dynamic, real-time probabilistic RUL estimation. This approach overlooks the integration of reliability distributions like Weibull for handling uncertainty in degradation trajectories and fails to leverage edge-cloud architectures for continuous covariate adaptation from live TPMS, OBD-II, and GPS streams, limiting its prognostic horizon to discrete failure snapshots [4].

2 Methodology

This chapter explains the development of a hybrid Predictive Maintenance framework that integrates Machine Learning (ML) with the Weibull reliability distribution to provide dynamic Remaining Useful Life (RUL) estimations. By treating the Weibull scale parameter (λ) as a dynamic covariate influenced by operational stressors, the model continuously adapts to the tire's specific degradation trajectory. The following sections detail the multi-layered methodology, encompassing high-fidelity data acquisition, rigorous preprocessing and feature engineering, the implementation of ensemble learning algorithms, and the specialized metrics used to evaluate the integrity of the predictive distributions.

2.1 Data acquisition

The data acquisition phase is the foundational layer of the predictive maintenance framework [5], designed to capture high fidelity telemetry from multiple vehicle subsystems. To achieve a comprehensive understanding of tire degradation, the system utilizes a multi sensor approach that monitors environmental, operational, and positional variables. By integrating localized sensor data with global positioning and engine diagnostics, the system creates a multidimensional view of the factors that accelerate tire wear.

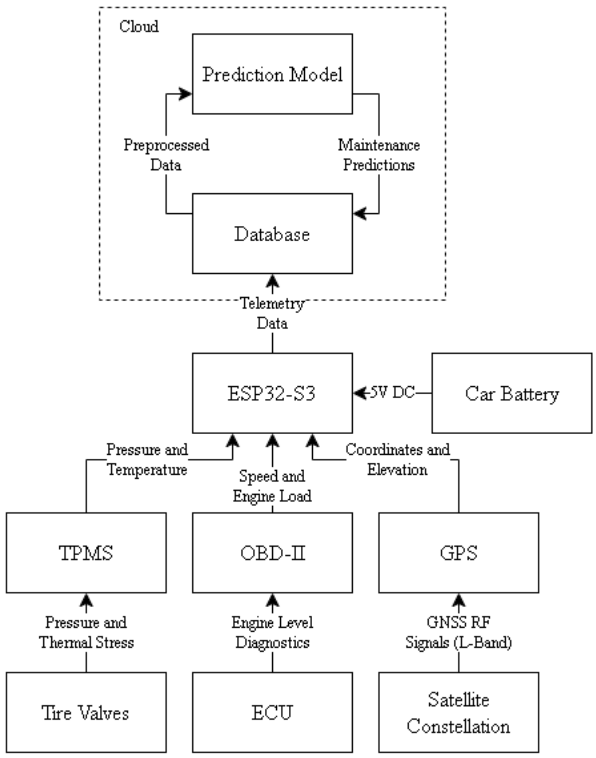

Fig 1. Data acquisition block diagram

The architecture follows a modular design centred around a microcontroller that acts as an edge gateway [6]. As shown in the block diagram above, the system interfaces with three primary external sources: the Tire Pressure Monitoring System (TPMS) via wireless communication, the On-Board Diagnostics (OBD-II) port via a specialized interpreter, and a Global Positioning System (GPS) module. This setup ensures that every data point from the heat generated inside the tire to the speed of the vehicle is logged for subsequent analysis.

Fig 2. ESP32-S3 DevKitC-1

The system relies on hardware components to facilitate data extraction and processing. ESP32-S3 Microcontroller, as shown in figure 2, will Serve as the central processing unit and edge gateway. It uses dual-core architecture to handle concurrent data streams and utilizes built in Bluetooth Low Energy (BLE) that will be used for to connect to OBD-II module and TPMS sensors [7].

Fig 3. FOBO Tire 2

FOBO Tire 2, as shown in figure 3, will be used to capture the pressure and thermal data of each tire. It is mounted directly on the tire valves, these sensors provide internal pressure and temperature readings. These variables are direct indicators of the physical stress and thermal load acting upon the tire structure during operation. While the FOBO Tire 2 system typically relies on a dedicated hardware receiver and a smartphone application for data visualization, this research bypasses those interfaces by implementing an ESP32-S3 edge gateway that utilizes a reverse-engineered methodology to decode the 13-byte payload structure within the 0x00EE Service Data UUID for direct, high-precision telemetry acquisition [8].

This specific TPMS gives heterogeneous sampling frequencies of the integrated sensor suite. While the GPS and OBD-II modules provide a constant telemetry stream, the FOBO Tire 2 sensors utilize an event-triggered transmission protocol to conserve battery life, broadcasting data only when significant pressure or temperature deltas are detected. This problem is fixed during the preprocessing phase using a forward fill data manipulation, which maps the last known tire variables to every constant observation point in the GPS and OBD-II logs. This approach ensures that each row in the time-series dataset contains a complete 13-column feature vector, representing a synchronized snapshot of both vehicle dynamics and tire thermodynamics.

Fig 4. ELM 327 Bluetooth

ELM 327 Bluetooth, as shown in figure 4, extracts engine level diagnostics from the vehicle's Engine Control Unit (ECU). By monitoring parameters such as engine load and vehicle speed, the system can correlate mechanical strain and driving intensity with the rate of tire degradation. Using Bluetooth communication between the ESP32-S3 edge gateway and the ELM327, the system retrieves real-time diagnostics, including speed and engine load, achieving a high-efficiency acquisition rate of 337.50 ms for six PIDs and a total cycle delay of 538.76 ms when factoring in display updates [9].

Fig 5. GPS Module U-blox NEO-M8N

U-blox NEO-M8N, as shown in figure 5, provides spatial context by tracking geospatial coordinates and elevation changes [10]. This data is essential for calculating cumulative mileage and identifying environmental stressors, such as road inclines or specific route characteristics that contribute to uneven wear.

The telemetry data captured during the field-testing phase is encapsulated in a structured dataset comprising 13 distinct parameters. The raw dataset includes geospatial data (Latitude, Longitude, and Altitude), vehicle dynamics (Speed and Engine Load), tire telemetry (pressure and temperature for each of four tires).

Fig 6. Digital Tread Depth Gauge

To establish a supervised learning environment, a target variable 'Tire Tread Depth' is acquired through physical measurement. Unlike the automated telemetry, tread depth is measured manually using a digital tread depth gauge, as shown in figure 6, with a resolution of 0.01 mm. The data collection process follows an average random sampling methodology, where 30 individual measurements are recorded per tire during each measurement session. These measurements are strategically distributed across two zones on the tire's circumference, separated by 180 degrees. Within each zone, the probe is placed randomly within a 5 cm radius along the outer main groove to account for localized wear variances, and the final value for the session is determined by calculating the average of all 30 points. To align these physical measurements with the real-time sensor data, we record by writing down the latest entry ID from the cloud database at the exact moment the manual measurements are taken.

Because these physical readings are collected periodically rather than continuously, the research utilizes linear interpolation based on cumulative distance to map the tread depth labels to every individual log in the telemetry stream. This process transforms discrete manual measurements into a continuous target variable, providing the high-resolution dataset required to train the machine learning models to recognize the complex correlations between operational stressors and the rate of tire degradation. First, the wear rate (scale) is determined between two measurement points:

$$scale = \frac{x_{previous} - x_{after}}{d_{after} - d_{previous}}$$

Then, the current interpolated tread depth (x) for a specific log entry is:

$$x = x_{previous} - \left(scale \times \left(d - d_{previous}\right)\right)$$

The current interpolated tread depth (x) is derived by evaluating the rate of wear between two physical measurement sessions. This process incorporates the manual tread depth measurement recorded at the start of the current interval ($x_{previous}$) and the measurement taken at the conclusion of that interval (x_{after}). The precise value of x at any given log entry is determined by the current cumulative distance captured by the GPS module (d), which is compared against the specific cumulative distances recorded at the moments $x_{previous}$ and x_{after} were obtained, represented as $d_{previous}$ and d_{after}, respectively.

To maintain a streamlined dataset, abbreviations are utilized to denote specific tire positions, a categorization that is critical for the Hybrid ML-Weibull prediction model to account for uneven wear patterns caused by vehicle weight distribution [11]. Within this structural framework, FR (Front-Right) and FL (Front-Left) represent the steer-axle tires on the driver's and passenger's sides, respectively. Correspondingly, RR (Rear-Right) and RL (Rear-Left) are used to identify the driver and passenger axle tires positioned behind the driver and passenger.

Each feature in the dataset is defined by specific units and serves a distinct role in the RUL estimation:

1. Timestamp: Recorded in UTC format (ISO 8601). This provides the temporal baseline for calculating the duration of stress events (e.g., how long a tire was subjected to high temperatures).
2. Latitude and Longitude (°): Recorded in Decimal Degrees. These coordinates allow for the calculation of cumulative mileage and the identification of road topography that may influence tire degradation.
3. Altitude (m): Represents the elevation above sea level, used to calculate road grade or incline, which directly impacts engine load and tire friction.
4. Speed (km/h): The instantaneous velocity of the vehicle, derived from the GPS and ECU sensors. High-speed cycles are associated with increased centrifugal force and heat generation within the tire carcass.
5. Engine Load (%): Represents the calculated percentage of peak available torque being utilized [12]. This serves as a proxy for the longitudinal force (traction or braking) applied to the tire treads.
6. Tire Pressure (PSI): Measured by the TPMS sensors. Deviations from the nominal cold pressure (under-inflation or over-inflation) are primary factors in accelerated shoulder or centre-rib wear.
7. Tire Temperature (°C): Monitors the internal air temperature of the tire. Excessive heat is a lead indicator of structural fatigue and rubber compound degradation.

The raw data captured by the integrated sensor suite requires a multi-stage refinement process to ensure it is suitable for predictive modelling. During the initial system power-on and sensor stabilization phase, the captured telemetry often contains significant noise and unstable readings. To eliminate these artifacts, the first 316 rows of each log were truncated. This truncation ensures that the subsequent machine learning training and testing phases only utilize data reflecting a stable operational state. To maintain the continuity of the time-series logs, specific geospatial and telemetry anomalies were addressed through localized corrections and imputation. The GPS module occasionally experienced signal dropouts, causing coordinates to reset to zero. For isolated single-point errors, values were corrected by calculating the average of adjacent valid coordinates. In instances of prolonged signal gaps, the system utilized path reconstruction by stitching together valid segments from the surrounding data to preserve the integrity of the route and mileage tracking. Similarly, intermittent signal loss from the TPMS sensors (which produced zero-value outputs during communication timeouts) was resolved using a combination of backward and forward fill techniques, as discussed before.

Final data preparation involved statistical outlier management and the transformation of raw coordinates into meaningful physical features. An Interquartile Range (IQR) method was applied to identify and clip non-representative spikes in velocity and distance data. To enforce domain-specific physical constraints, any log showing an incremental distance shift exceeding 1000 meters (a distance physically impossible for standard vehicle travel between consecutive timestamps) was flagged as flawed and removed from the set.

2.2 Dataset

The raw telemetry data harvested from the edge devices must undergo a transformation process to be utilized effectively in a predictive framework. This phase involves aligning disparate data streams often arriving at different frequencies and containing environmental noise into a cohesive, time-series structure. By converting raw physical signals into mathematically significant features, the system creates a dataset that accurately represents the degradation lifecycle of the tire under varying operational conditions [13].

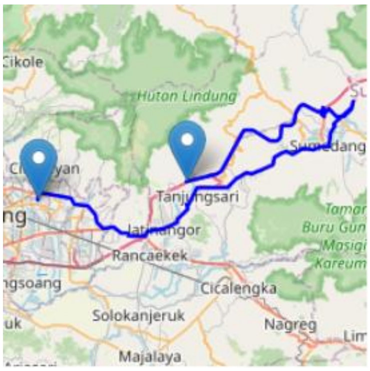

Fig 7. Map of preprocessed travel sample

The visualization on figure 7 presents a sample of the cleaned dataset acquired. At this stage, the data has been synchronized into a uniform time-series format where each row represents a discrete observation point. This structured view allows for a clear observation of the relationship between vehicle movement and the corresponding sensor responses.

The dataset is composed of several feature variables, each derived from the sensor suite through specific computational logic and imputation techniques:

1. Distance Travelled (Δd): Calculated as the Haversine distance between the current and previous GPS coordinates, measured in meters. This represents the incremental work performed by the tire between observation points [14].
2. Elevation Travelled (Δh): Determined by the difference between the current and previous GPS altitude readings. Positive values indicate an incline, whereas negative values signify a decline in vehicle elevation. This feature helps the model account for

gravitational loads and the increased friction associated with incline or decline driving [15].

3. Engine Load and Speed (L, V): Extracted directly from the OBD-II interface. These parameters indicate the mechanical intensity and kinetic energy of the vehicle, which are primary drivers of frictional wear [16].

4. Side (S): A categorical feature used to differentiate which specific tire (e.g., FR, RL) the data point belongs to, allowing the model to account for uneven weight distribution or alignment variances. The indexing is defined as: S=0 for FR, S=1 for FL, S=2 for RR, and S=3 for RL.

5. Pressure and Temperature (P, T): Sourced from the TPMS sensors via BLE for each tire. To conserve battery, these sensors only transmit data when a significant delta is detected, resulting in numerous null values in the raw logs. We resolve this by applying a forward fill strategy to maintain a continuous state of tire inflation and thermal conditions across observations.

6. Previous Degradation (D_{t-1}): A recursive feature representing the last known state of tire wear, measured in nanometres. This is introduced to support the continuous-time observation model, allowing the algorithm to understand that current wear is a function of the cumulative damage history.

Table 1. Preprocessed Data Sample

Δd	Δh	L	V	S	P	T	D_{t-1}	D
1.548	0.1	60.000	3	0	28.861	35	1.53	1.53
2.577	0.3	81.568	1	0	28.861	35	1.53	1.53
2.146	0.7	62.352	1	0	28.861	35	1.53	1.53
1.015	0.9	59.607	1	0	28.861	35	1.53	1.53
1.821	0.4	84.705	1	0	28.861	35	1.53	1.53

As shown in the target variable visualization on Figure 8, the Tire Tread Depth exhibits a clear trend as mileage increases, though the rate of decay based heavily on the operational features. As discussed before, these "ground truth" labels are interpolated between physical measurement points to provide a continuous training signal.

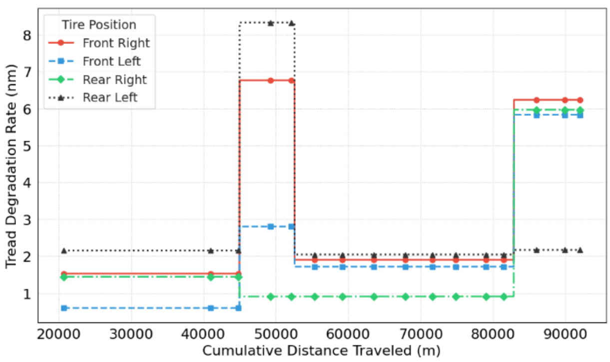

Fig 8. Tire depth thread degradation graph sample

This mapping allows the machine learning models to learn how specific events such as a high load climb at high temperatures accelerate the slope of the degradation curve compared to steady state cruising [17]. The application of linear interpolation between periodic measurement points results in a constant tread degradation rate over extended distances within each specific log interval.

To ensure the efficiency of the machine learning algorithms, particularly for gradient based optimizers, Standard Scaling is applied to the feature set [18]. Since the input variables exist in vastly different units ranging from pressure in PSI to elevation in meters, raw values could cause the model to over-prioritize features with larger magnitudes. By transforming each feature to have a mean of zero and a standard deviation of one, it stabilizes the learning process and allow the machine learning models to converge faster while accurately weighting the contribution of each sensor input regardless of its original scale. This dataset will be split into 80% of training dataset and 20% of testing dataset.

2.3 Prediction models

The prediction framework developed in this research employs a hybrid architecture that integrates Machine Learning (ML) with the Weibull reliability distribution to overcome the limitations of static maintenance modelling [19]. The formula of Weibull Cumulative Distribution Function (CDF) to calculate the probability of failure is as follows:

$$f(t; \lambda, k) = \frac{t}{\lambda}\left(\frac{k}{\lambda}\right)^{k-1} e^{-(t/\lambda)^k}$$

At the core of this approach is the concept of a covariate-driven scale parameter, where the characteristic life of the tire, denoted as λ, is treated as a dynamic variable rather than constant [20]. This allows the model to respond to real-time changes in the feature vector and the individual pressure and temperature readings for the four wheels. By mapping these specific stressors to the scale parameter, the system can estimate how current driving behaviours either accelerate or decelerate the tire's degradation process.

The implementation of this hybrid model uses four distinct algorithms to ensure the highest degree of predictive accuracy. These include the No Covariate model where the stressor or covariates will not be accounted showing the default performance of Weibull Distribution, statistical Accelerated Failure Time (AFT) model using Ordinary Least Squares (OLS) as a linear regression model, and advanced ensemble methods such as XGBoost and LightGBM. LightGBM is particularly emphasized in this research due to its leaf-wise growth strategy, which allows it to capture the complex, non-linear relationships between vehicle telemetry and tire wear more effectively than traditional linear regressions. These algorithms are trained to predict the scale parameter λ for each tire based on its specific sensor index, where the system identifies the FR tire as index 0, FL as index 1, RR as index 2, and RL as index 3. This indexing is crucial because it allows the model to account for position-specific stress factors, such as the increased thermal load on steering tires versus the torque stress on drive-axle tires.

Once the ML regressor predicts the dynamic scale parameter, it is integrated into the Weibull CDF to provide a probabilistic RUL estimation. The final RUL is then derived by calculating the temporal or mileage-based distance between the current operating state and the point where the reliability curve reaches a threshold. This methodology ensures that the prediction is not just a single point in time, but a distribution that accounts for the inherent uncertainty in mechanical degradation and varying road conditions.

2.4 Evaluation models

The evaluation of the hybrid model is conducted through a multi-layered strategy that assesses both the accuracy of the point-wise RUL predictions and the integrity of the predicted reliability distributions. To measure the absolute performance of the ML regressors, standard statistical metrics including Mean Absolute Percentage Error (MAPE), Symmetric MAPE (SMAPE), and Mean Absolute Scaled Error (MASE) are employed. These metrics are essential for determining the deviation between the predicted life expectancy and the actual ground truth, specifically helping to identify if the model's error remains within an acceptable range for automotive safety applications [21]. MAPE measures the accuracy of a model by calculating the average absolute percent error between the predicted values (p_i) and the actual ground truth values (y_i) at index i. The formula for MAPE is as follows:

$$MAPE = \frac{100}{n}\sum_{i=0}^{n}\left|\frac{y_i - p_i}{y_i}\right|$$

Let n be the number of test dataset. SMAPE is a variation of MAPE that provides a "symmetric" measure of error by including both the actual and predicted values in the denominator. The formula for SMAPE is as follows:

$$SMAPE = \frac{200}{n}\sum_{i=0}^{n}\frac{|y_i - p_i|}{|y_i| - |p_i|}$$

In these evaluation metrics, n refers to the total number of test data points used to assess the model's accuracy. MASE is especially significant in this context as it compares the hybrid model's performance against a naive forecasting baseline, proving whether the inclusion of sensor telemetry significantly improves the predictive power. The formula for MASE is as follows:

$$MASE = \frac{1}{n}\sum_{i=0}^{n}\left|\frac{y_i - p_i}{\frac{1}{n-1}\sum_{i=2}^{n} y_i - y_{i-1}}\right|$$

Beyond standard regression analysis, this research introduces specialized area-based metrics to evaluate the performance of the Weibull distribution. These include Mean Weibull Error (MWE) and Mean Quadratic Weibull Error (MQWE), which calculate the area difference between the predicted continuous CDF and the actual step-function of the failure event. By measuring the error area rather than just a single time point, these metrics provide a better view of how well the model captures the probability of failure over time. The formula for MWE is as follows:

$$MWE = \frac{1}{n}\sum_{i=1}^{n} WE(y_i, p_i, k)$$

Where

$$WE(y_i, p_i, k) = y_i + \frac{2p_i}{k}\Gamma\left(\frac{1}{k}, \left(\frac{y_i}{p_i}\right)^k\right) - \frac{p_i}{k}\Gamma\left(\frac{1}{k}\right)$$

In this formula p_i replaces λ, as it is now a dynamic value that are different on each index i. The predicted continuous Weibull CDF, utilizing the predicted scale parameter $\lambda = p_i$ is evaluated against the actual failure event represented as a step function at the ground truth y_i. Mean Left Weibull Error (MLWE) represents "pessimistic" errors, where the model predicts a failure earlier than it occurs, which can lead to premature maintenance and increased operational costs. The formula for MLWE is as follows:

$$MLWE = \frac{1}{n}\sum_{i=1}^{n} LWE(y_i, p_i, k)$$

Where

$$LWE(y_i, p_i, k) = y_i + \frac{p_i}{k}\Gamma\left(\frac{1}{k}, \left(\frac{y_i}{p_i}\right)^k\right) - \frac{p_i}{k}\Gamma\left(\frac{1}{k}\right)$$

Mean Right Weibull Error (MRWE) represents "optimistic" errors, where the model predicts a longer life than the tire can provide, presenting a direct threat to passenger safety. The formula for MRWE is as follows:

$$MRWE = \frac{1}{n}\sum_{i=1}^{n} RWE(y_i, p_i, k)$$

Where

$$RWE(y_i, p_i, k) = \frac{p_i}{k}\Gamma\left(\frac{1}{k}, \left(\frac{y_i}{p_i}\right)^k\right)$$

MQWE is particularly useful for safety systems as it applies a quadratic penalty to large discrepancies, effectively forcing the model to minimize high-risk errors that could lead to catastrophic tire failure. The formula for MQWE is as follows:

$$MQWE = \frac{1}{n}\sum_{i=1}^{n} QWE(y_i, p_i, k)$$

Where

$$QWE(y_i, p_i, k) = y_i + \frac{2p_i}{k}\Gamma\left(\frac{1}{k}, \left(\frac{y_i}{p_i}\right)^k\right) - \frac{p_i}{k}\Gamma\left(\frac{1}{k}\right) + \frac{p_i}{k2^{1/k}}\Gamma\left(\frac{1}{k}\right)$$

All these evaluations are validated against a ground truth dataset derived from manual tread depth measurements taken with a digital gauge, which are then synchronized with the continuous telemetry logs through linear interpolation to provide a high-resolution reference for every data point captured.

3 Results and discussion

The results and discussion chapter provides a comprehensive analysis of the field test data and the subsequent performance of the hybrid prediction models. The primary objective is to evaluate the efficacy of integrating real-time vehicle telemetry with the Weibull reliability framework to predict tire maintenance needs accurately. This section details the characteristics of the captured data, the behavior of key stress factors during operation, and a comparative analysis of the machine learning algorithms in estimating the RUL of the tires. By examining the correlation between vehicle dynamics and tire thermodynamics, this discusses how the proposed system transforms raw sensor outputs into actionable safety metrics.

Table 2. Prediction Performance

Evaluation Models	Prediction Models			
	No Covariate	AFT OLS	XGBoost	LightGBM
MAPE (%)	0.75	0.142	0.003	0.002
SMAPE (%)	0.555	0.141	0.003	0.001
MASE (%)	67.064	18. 829	0.3112	0.216
MWE (m)	31.147	24.918	23.609	23.603
MQWE ($x10^8$ m)	10.87	8.99	7.74	7.53
MLWE (m)	18.211	13.754	13.895	13.904
MRWE (m)	12.913	11.098	9.668	9.652

The quantitative performance of the evaluated models is summarized in Table 2, where the superiority of covariate-driven models over the "No Covariate" baseline is clear. The baseline model, which relies on static historical averages, exhibits the highest error across all metrics, with a MAPE of 0.7508 and a MASE of 67.0644. In stark contrast, the transition to ensemble learning methods results in a drastic reduction in error. LightGBM emerged as the top-performing model, achieving a near-negligible MAPE of 0.0025 and a MASE of 0.2168. This represents a massive improvement in precision, indicating that the leaf-wise growth strategy of LightGBM is exceptionally capable of capturing the complex, non-linear relationships between vehicle stress factors and tire wear that linear model like AFT-OLS ($MAPE = 0.1426$) fail to fully resolve.

Beyond standard regression metrics, the reliability-specific area metrics (MWE and MQWE) further validate the hybrid approach. The LightGBM model reduced MWE to 23.603 meters, compared to 31.147 meters for the baseline, representing a significant tightening of the probability distribution around the actual failure event. The MQWE for LightGBM ($7.53 \times 10^8 m$) is lower than the baseline ($10.87 \times 10^8 m$), demonstrating that the machine learning approach effectively minimizes large, high-risk outliers. This reduction in the "error area" signifies that the model provides a more confident and stable reliability curve, which is essential for a safety application like tire maintenance.

4 Conclusion

This research successfully develops a hybrid predictive maintenance framework that directly addresses the safety risks and technical limitations identified in current tire monitoring technologies. While tire failure remains a significant contributor to road fatalities (accounting for 3-15% of fatal accidents globally and hundreds of annual deaths in the US) conventional TPMS remain limited by their reactive nature. The proposed Hybrid ML-Weibull system overcomes these deficiencies by transitioning from simple under-inflation detection to a proactive and real-time RUL estimation.

By integrating live telemetry from TPMS, OBD-II, and GPS modules through an edge-cloud architecture, the system provides a continuous prognostic horizon that accounts for the dynamic stressors (such as pressure and temperature fluctuations) that are often neglected in static or simulation-centric models. The implementation of this system effectively fills the gaps found in existing research, specifically moving beyond the aggregated, historical data approach of the Honda RI work and the static classification focus of FusionNet. By utilizing the ESP32-S3 as a high-fidelity edge gateway, the research achieves a synchronized data stream that captures the immediate impacts of engine load and vehicle speed on tire degradation. The integration of the Weibull distribution into the machine learning pipeline addresses the need for probabilistic modeling and uncertainty handling, which was identified as a key missing component in previous deep learning frameworks. The empirical results validate this hybrid approach, as the LightGBM model showed a superior ability to capture complex, non-linear relationships, achieving a near-negligible MAPE of 0.0025 compared to the much higher errors seen in baseline and linear models.

This study shows that a covariate-driven reliability model provides a significantly more accurate and stable prediction curve for safety tire maintenance. The use of specialized area-based metrics like MQWE confirms that the machine learning approach effectively minimizes high-risk outliers, while the analysis of MLWE and MRWE ensures a pessimistic error profile that prioritizes passenger safety by prompting maintenance before catastrophic failure. By providing a scalable solution for real-time, in-vehicle PHM, this research offers a robust pathway to reducing tire-related road casualties and advancing the state of modern vehicle health monitoring systems.

Future research should prioritize the development of automated, real-time tire tread depth measurement systems to replace the current reliance on periodic manual ground truth acquisition. By integrating high-precision depth sensors directly into the vehicle's telemetry stream alongside OBD-II and GPS modules, researchers can achieve a fully autonomous data acquisition pipeline. Furthermore, future studies should implement advanced TPMS sensors capable of continuous, high-frequency pressure and thermal data streaming rather than event-triggered protocols that are only reactive to specific environmental deltas. These advancements would eliminate the need for manual sampling sessions and the subsequent requirement for linear interpolation or forward fill data manipulation for state alignment, providing a more synchronized dataset. Such an integrated telemetry approach is essential for enhancing the precision of dynamic RUL estimations and advancing the overall robustness of in-vehicle PHM systems.

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