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Brake Tire Sense-AI: An Artificial Intelligence-Based Smart Diagnostic Framework for Early Detection of Brake and Tire Failures in Commercial Trucks to Reduce Severe Highway Accidents

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Background: Brake and tire defects remain major safety concerns in vehicles. Conventional inspection and fixed-threshold monitoring can identify established defects but may miss early, multivariable patterns of deterioration. Artificial intelligence (AI), multimodal sensing and edge analytics may permit earlier identification of safety-critical mechanical degradation.

Objective: To prospectively develop and validate Brake Tire Sense-AI, a multimodal AI framework for early detection of major brake and tire defects in heavy commercial trucks and for generation of interpretable component-level risk alerts.

Methods: A prospective multicenter engineering diagnostic-accuracy cohort is proposed involving 530 heavy commercial trucks operated in Pakistan and the USA over 12 months. Brake pressure, brake temperature, wheel-speed, vibration, tire pressure, tire temperature, vehicle-load, environmental and computer-vision data will be acquired through an edge gateway. AI pipeline will combine supervised classification, temporal modeling, anomaly detection and multimodal sensor fusion. Mechanical inspection and documented maintenance findings will serve as the reference standard.

Sample Size: Using the Buderer diagnostic-test framework, assuming an anticipated sensitivity of 90%, 95% confidence level, precision of ±7%, and an estimated 15% prevalence of defect-positive trucks, approximately 471 evaluable trucks are required; allowing 10% incomplete or unusable follow-up gives 523, rounded to a proposed enrollment target of 530 trucks.

Statistical Analysis: Descriptive statistics will characterize trucks, routes, duty cycles and defect events. Diagnostic accuracy will be reported with 95% confidence intervals. AUROC and precision-recall curves will assess discrimination; calibration plots and Brier score will assess calibration. Vehicle-level bootstrapping and cluster-robust methods will account for repeated episodes. Comparisons with conventional threshold-based monitoring will use paired methods where appropriate. Time-to-defect after an alert will be assessed using survival models, and false-alert burden will be reported per distance traveled.

Results: Illustrative results: In the simulated 530-truck cohort, 82 trucks (15.5%) experienced at least one adjudicated major brake or tire event. In the locked test set, Brake Tire Sense-AI identified 12 of 13 events, corresponding to 92.3% sensitivity, 92.4% specificity, 98.4% negative predictive value and AUROC 0.95. The simulated operational comparison also showed fewer roadside brake/tire breakdowns and lower maintenance downtime during AI-assisted monitoring. These values are illustrative and require prospective empirical validation.

Keywords: Artificial Intelligence (AI), Commercial Trucks, Brake Failure, Predictive Maintenance, Deep Learning, Sensor Fusion

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1. Introduction

Heavy commercial trucks are complex cyber-physical systems in which braking, tire-road interaction, suspension, wheel-end dynamics, vehicle mass, road geometry and environmental conditions interact continuously. From an engineering perspective, a brake or tire defect should therefore be treated as a time-varying degradation process rather than a binary inspection finding. Loss of braking torque, thermal imbalance, pneumatic leakage, abnormal wheel-end vibration, tire under-inflated or structural damage can evolve over hundreds or thousands of kilometers before a conventional inspection identifies a safety-critical condition.

The regulatory environment provides an important engineering reference layer. U.S. inspection data show that brake and tire deficiencies remain recurrent fleet-level problems [2-4]. In parallel, Pakistani motorway research has identified tire bursting as a significant crash predictor in commercial-vehicle operations [31]. These observations support a condition-monitoring architecture that measures component state continuously and estimates degradation trajectories instead of relying solely on periodic inspection.

Conventional controls—including pre-trip inspection, scheduled maintenance, roadside inspection, tire-pressure monitoring and ABS/EBS diagnostics—remain mandatory safety barriers. However, they are generally discrete observations or threshold-triggered responses. An engineering diagnostic system can complement them by sampling component-state variables continuously, extracting temporal features, normalizing measurements for load and environment, and estimating the probability that a defect will cross a critical operating limit.

Recent literature has increasingly examined brake fault detection, predictive maintenance, digital twins, sensor fusion and AI-supported tire inspection [6-14]. Reviews of vehicle predictive maintenance highlight the potential of machine learning but emphasize unresolved issues involving data scarcity, domain shift, generalizability, explainability and real-world validation [7,8]. A recent systematic review specifically focused on heavy-vehicle brake failure reported increasing use of sensing and AI but noted that real-road validation remains limited [6].

Brake Tire Sense-AI is therefore designed as a layered cyber-physical diagnostic system: sensors and vehicle networks acquire physical-state data; an edge computer performs signal conditioning and feature extraction; AI models estimate component health; a fusion engine computes system-level risk; and a fleet platform schedules engineering inspection and predictive maintenance. The driver remains the final operational decision-maker and the AI layer does not replace statutory inspection or vehicle control systems.

1.1. Pakistan–USA Engineering and Road-safety context

Brake Tire Sense-AI is intended for deployment across heterogeneous commercial-vehicle environments. Pakistan and the United States provide useful contrasting engineering contexts for evaluation because they differ in fleet composition, road infrastructure, inspection regimes, climate exposure and availability of vehicle telemetry.

In Pakistan, WHO estimated the road-traffic mortality rate at 11.9 deaths per 100,000 population in 2021. A motorway-based analysis of 1,110 crashes recorded by the National Highways and Motorway Police on the M1 and M2 during 2013–2017 found that 31% of commercial-vehicle crashes were fatal and identified tire bursting as a significant predictor of crashes, alongside drowsy driving, poor road conditions and over speeding [31,32]. These findings support an engineering requirement for continuous tire-condition assessment rather than reliance only on periodic inspection. Pakistan's road environment also provides an important test case for robustness to high ambient temperatures, mixed road quality, heavy loading, long-distance freight operations and variable maintenance conditions.

In the United States, FMCSA reported that 5,837 large trucks were involved in fatal crashes and approximately 120,000 large trucks were involved in injury crashes in 2022 [1]. Current FMCSA crash-query data also provide a continuing national surveillance infrastructure for commercial-motor-vehicle crashes, while CVSA inspection programs demonstrate the persistence of brake and tire deficiencies in the operating fleet [2-4]. The engineering challenge in the U.S. setting is therefore not only detection of gross defects but also early identification of degradation across large fleets with heterogeneous vehicle configurations and extensive telematics.

These country differences motivate a domain-adaptive engineering architecture. The core diagnostic variables—brake pressure, brake temperature, wheel speed, vibration, tire pressure, tire temperature, tread condition and vehicle load—should remain standardized, whereas model calibration should account for climate, road grade, axle loading, duty cycle, tire specification and maintenance practices. Cross-country validation should therefore use country-stratified performance estimates and external validation rather than assuming that a model trained in one fleet will transfer unchanged to another.

2. Study Objectives and Hypotheses

2.1. Primary Objective

To determine the diagnostic performance of Brake Tire Sense-AI for early prediction of a confirmed major brake or tire defect in heavy commercial trucks during routine real-world operation.

2.2. Secondary Objectives

- Compare Brake Tire Sense-AI with conventional fixed-threshold and scheduled-inspection approaches.
- Quantify warning lead time before confirmed mechanical diagnosis.
- Estimate the false-alert burden per 10,000 km and per 1,000 vehicle-days.
- Evaluate calibration and uncertainty of the composite Brake-Tire Safety Risk Score (BTSRS).
- Determine whether model performance is preserved across truck manufacturers, axle configurations, duty cycles, environmental conditions and fleet sites.
- Explore associations between AI alerts and roadside breakdowns, unplanned maintenance, downtime, near-miss events and brake/tire-related safety incidents.
- Evaluate explain ability outputs to determine whether predicted risk is supported by mechanically plausible sensor contributions.

2.3. Hypotheses

The primary hypothesis is that the locked BrakeTireSense-AI model will achieve sensitivity of at least 90% for confirmed major brake/tire defects within the predefined prediction horizon while maintaining clinically/operationally acceptable specificity and false-alert burden. A secondary hypothesis is that multimodal fusion will provide superior discrimination and earlier warning than single-sensor or fixed-threshold monitoring alone.

3. Materials and Methods

3.1. Study Design

This will be a prospective, multicenter diagnostic-accuracy cohort study with embedded AI model development and prospective silent validation. Participating trucks will undergo 12 months of continuous telemetry monitoring together with scheduled and event-triggered mechanical inspections. The study will follow relevant reporting principles for diagnostic prediction modeling and will pre-specify the algorithm-development pipeline before the locked test set is analyzed.

3.2. Study Setting

The proposed study will recruit trucks from at least three commercial fleet sites representing different duty cycles and route characteristics. Sites should include a combination of long-haul and regional operations and, where feasible, variation in road gradient and ambient temperature. Fleet maintenance facilities must be able to document standardized inspection findings and component replacements.

3.3. Eligibility Criteria

Inclusion Criteria

- Heavy commercial truck with gross vehicle weight rating approximately ≥11,794 kg (26,000 lb) or the locally equivalent heavy-vehicle classification.
- Operational ABS/EBS and electronic vehicle network capable of exposing relevant telemetry through SAE J1939/CAN or equivalent.
- Expected fleet availability for at least 9 months during the 12-month study.
- Permission for installation of study sensors and secure retrieval of telemetry and maintenance data.
- Baseline certified brake and tire inspection completed before study activation.

Exclusion Criteria

- Vehicle already scheduled for permanent retirement within 3 months.
- Unresolved baseline critical brake/tire defect at study entry.
- Major modification preventing standardized sensor installation or signal interpretation.
- Persistent inability to synchronize telemetry, inspection and maintenance records.
- Use primarily in off-road service if the intended target population is highway freight operation.

Table 1: Pakistan–USA engineering context for Brake Tire Sense-AI deployment

Engineering Domain	Pakistan context	USA context	Brake Tire Sense-AI implication
Road-safety burden	WHO road-traffic mortality rate 11.9/100,000 (2021); motorway study found 31% of commercial-vehicle crashes fatal [31,32]	5,837 large trucks involved in fatal crashes and ~120,000 in injury crashes in 2022 [1]	Use safety-critical early-warning design and country-stratified validation
Vehicle defects	Tire bursting was a significant crash predictor in M1/M2 motorway data [31]	Brake and tire defects remain prominent in CVSA inspections [2-4]	Prioritize tire pressure/temperature, wheel-end vibration and brake thermal asymmetry
Operating environment	High thermal exposure, variable road quality, mixed loading and maintenance conditions	Highly heterogeneous fleets, long-haul routes, extensive telematics and regulated inspection	Use context-aware normalization and domain adaptation
Data architecture	Potentially greater dependence on retrofit sensors and edge processing	Greater availability of CAN/ECU/telematics data	Support both retrofit and native vehicle-network configurations

Table 2: Proposed Study Design and Operational Definitions

Element	Proposed specification
Design	Prospective multicenter diagnostic-accuracy cohort with AI model development and locked test evaluation
Population	Heavy commercial trucks used for long-haul, regional-haul or mixed freight operations
Sample	530 enrolled trucks
Follow-up	12 months per truck or until permanent withdrawal from participating fleet
Primary index test	Brake Tire Sense-AI composite risk model
Reference standard	Blinded certified mechanical inspection plus maintenance-confirmed defect classification
Primary event	Major brake or tire defect requiring urgent repair, removal from service, or judged unsafe for continued operation
Prediction horizon	Within 7 days or 500 km after an AI alert, whichever occurs first
Primary performance measure	Sensitivity on the locked test cohort
Major secondary measures	Specificity, AUROC, PPV, NPV, calibration, lead time, false alerts/10,000 km, breakdowns and downtime

3.4. Sample Size Calculation

The sample size is based on precision of the primary diagnostic-performance endpoint. Using the method described by Buderer [23], the number of defect-positive vehicles required to estimate an anticipated sensitivity (Se) of 0.90 with a two-sided 95% confidence interval and half-width (d) of 0.07 is:

$$\mathbf{n\_defect = Z^2 \times Se \times (1 - Se) / d^2 = 1.96^2 \times 0.90 \times 0.10 / 0.07^2 \approx 71 \text{ defect-positive trucks}}$$

Assuming approximately 15% of monitored trucks experience at least one confirmed major brake/tire defect during follow-up, 71/0.15 ≈ 471 evaluable trucks are required. Allowing approximately 10% incomplete follow-up, sensor failure or unusable reference-standard data yields 471/0.90 ≈ 523 trucks. The proposed enrollment target is therefore rounded to 530 trucks. If the observed defect prevalence is substantially below 15%, follow-up should be extended or additional trucks recruited until at least 71 defect-positive vehicles are accrued for primary sensitivity estimation.

3.5. Brake Tire Sense-AI Sensing Platform

The framework will combine existing vehicle-network signals with additional study-grade sensors where necessary. All sensors will be timestamp-synchronized to a common clock.

Critical safety functions such as ABS/EBS will not be modified by the research system; Brake Tire Sense-AI will operate as a monitoring and advisory layer during model development and silent validation.

3.6. Data Acquisition and Edge Processing

Vehicle-network integration will follow the SAE J1939 architecture where applicable [30]. An onboard edge gateway will acquire and synchronize signals, apply range checks and plausibility filters, flag missing, compute selected rolling-window features and execute the locked inference model. Critical alerts must remain available without cloud connectivity. Encrypted summary packets will be transmitted to the fleet research server when connectivity is available.

Raw high-frequency data will be retained for predefined anomalous episodes and a sampled proportion of normal operation; lower-frequency summary features will be stored continuously to control data volume. All timestamps will use a standardized time base and vehicle identifiers will be pseudonymized before analysis.

3.7. Tire Computer-Vision Assessment

At baseline and at scheduled depot visits, standardized tire images will be captured under controlled lighting. Where operationally feasible, an automated inspection-gate camera may be used. Transfer learning and deep convolutional models have shown promise for tire crack and defect detection [9-13]. Candidate visual outputs will include normal condition, low tread, irregular wear, tread or sidewall cracking, cut, bulge, suspected separation and foreign-object penetration. Visual AI predictions will be treated as a component of the fused model rather than a definitive mechanical diagnosis.

3.8. Ground-Truth Reference Standard

The reference standard will be a structured mechanical assessment performed by a certified inspector or qualified fleet technician blinded, where feasible, to the numerical AI risk score. Each suspected event will be classified using predefined criteria as no significant defect, minor defect, major defect, or critical/out-of-service defect. Ground truth will include direct inspection measurements, repair findings, removed-component inspection, maintenance work order and, when relevant, roadside inspection documentation.

3.9. AI model Development

The machine-learning pipeline will be developed using a vehicle-level split to prevent leakage of observations from the same truck across training and testing. Approximately 70% of enrolled trucks will form the development set, 15% the validation set and 15% a locked test set. Site and truck-make stratification will be used where feasible so that the test set remains representative.

Candidate structured-data models will include logistic regression as a transparent baseline, random forest [15], gradient boosting and support-vector machine [16]. Longitudinal signal windows will be evaluated with long short-term memory or related sequence models [17]. Tire images will be analyzed using residual convolutional networks [18] and real-time object-detection architectures derived from YOLO [19]. The final model may use an ensemble combining structured, temporal, vision and engineering-rule outputs.

Class imbalance will be addressed using class-weighted losses, careful event-window sampling and anomaly detection rather than indiscriminate duplication of rare critical events. Model selection will prioritize sensitivity, calibration and false-alert burden rather than overall accuracy alone.

3.10. Multimodal Fusion and Brake-Tire Safety Risk Score

Each modality will generate calibrated component probabilities. Brake and tire probabilities will be combined with contextual variables such as load, speed, gradient, environmental conditions, persistence of abnormal signals and model uncertainty to produce the Brake-Tire Safety Risk Score (BTSRS). The action threshold will be selected on the validation set before test-set un-blinding. A lower advisory threshold may be used for maintenance planning, while the primary diagnostic analysis will use a single pre-specified action threshold.

3.11. Explainable AI

Model outputs will include component-level explanations. SHAP values will be used for global and local feature-attribution analysis [20], and LIME may be used as a sensitivity/interpretability comparator [21]. Explanations will be mapped to mechanically meaningful statements, for example persistent left-right brake temperature divergence, accelerating pressure loss or repeated abnormal tire-temperature/pressure coupling. Explainability is intended to support human review and does not replace mechanical diagnosis.

3.12. Digital-Twin and Remaining-Life Exploratory Analysis

An exploratory vehicle-health state representation will integrate cumulative distance, thermal exposure, heavy-braking episodes, tire pressure history, component age and prior repairs. Digital-twin research in tire and ground-vehicle maintenance suggests that combining physical history with machine learning can support remaining-life estimation [14,25]. Remaining useful life will therefore be evaluated as an exploratory outcome and will not be used to authorize continued operation of a vehicle with a critical alert.

Table 3: Proposed Sensor Variables and Diagnostic Role

Domain	Variables	Purpose
Brake	Brake chamber/line pressure; pressure build-up and loss rate	Detect insufficient actuation, leakage and abnormal response
Brake	Disc/drum or wheel-end temperature; left-right asymmetry	Detect overheating, drag and asymmetric braking
Brake	Pad/lining wear where electronically available	Quantify friction-material deterioration
Brake	Wheel-end vibration / accelerometer features	Detect abnormal mechanical vibration and change over time
Brake	ABS/EBS fault codes and intervention events	Characterize electronic/system abnormality
Tire	Inflation pressure and rate of pressure loss	Detect under inflated, leakage and imbalance
Tire	Tire temperature and thermal asymmetry	Identify abnormal thermal loading
Tire	Tread depth / maintenance measurements	Provide direct wear ground truth
Tire	Standardized tread and sidewall images	Detect cracks, cuts, bulges and irregular wear using computer vision
Vehicle	Wheel speed, vehicle speed, acceleration, braking demand	Provide dynamic context and indirect wear information
Vehicle	Axle/vehicle load where available	Adjust expected operating ranges for load
Environment	Ambient temperature, rain status and road gradient	Contextualize thermal and traction-related signals
History	Mileage, component age, prior repairs, replacement dates	Support degradation and remaining-life estimation

Table 4: Proposed Outcome Definitions

Outcome	Operational definition
Major brake defect	Defect requiring urgent repair or removal from normal service, including significant brake imbalance, severe friction-material wear, air-system leakage, persistent abnormal drag/overheating, drum/rotor damage, or equivalent certified finding
Major tire defect	Unsafe or urgent-repair condition including severe underinflation/leak, insufficient tread, exposed cord, major cut/bulge, suspected separation, critical cracking, or equivalent certified finding
True-positive alert	BTSRS exceeds prespecified action threshold and a major brake/tire defect is confirmed within 7 days or 500 km
False-positive alert	Action-threshold alert without a confirmed major defect in the prediction window after adjudication
False negative	Confirmed major defect with no qualifying AI alert during the prediction window before diagnosis
Warning lead time	Time and distance between first qualifying alert and confirmed defect diagnosis
Roadside breakdown	Unplanned vehicle stoppage requiring roadside service/tow for a brake- or tire-related cause
Near-miss safety event	Fleet-defined safety event attributed by blinded adjudication to brake/tire condition without a reportable collision

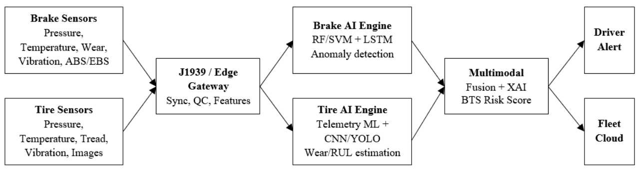

Figure 1: Proposed Brake Tire Sense-AI multimodal architecture

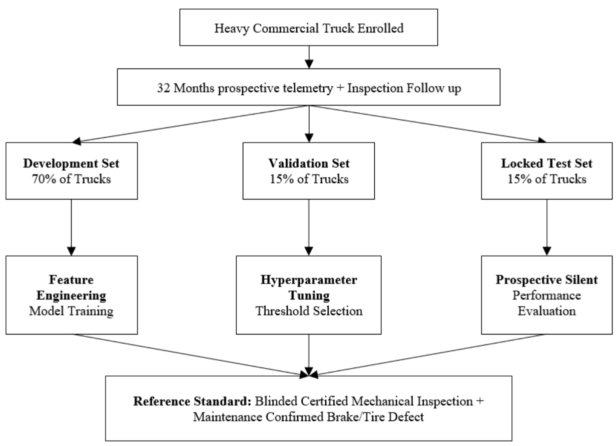

Figure 2: Pre-specified AI development and statistical evaluation pipeline

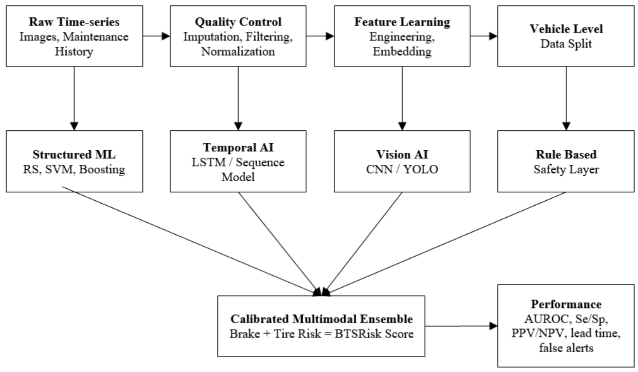

Figure 3: Pre-specified AI development and statistical evaluation pipeline

3.13. Cyber Security, Safety and Governance

The research system will be isolated from primary brake-control authority. Development will consider ISO 26262 functional-safety principles [28] and ISO/SAE 21434 cyber security engineering principles [29]. Secure boot, signed firmware, encrypted transmission, role-based dashboard access, audit logging and plausibility checks will be implemented. The AI system will never suppress conventional ABS/EBS/TPMS warnings or mandatory inspections.

4. Statistical Analysis Plan

Analyses will be conducted using a pre-specified statistical analysis plan finalized before the locked test set is opened. The vehicle will be the primary independent unit for data partitioning; repeated alerts and events within a vehicle will be handled using clustered or mixed-effects methods.

4.1. Primary Endpoint Analysis

The primary analysis will estimate sensitivity of the pre-specified BTSRS action threshold for a confirmed major brake or tire defect occurring within 7 days or 500 km after the alert. If a vehicle has multiple qualifying defect episodes, the first event will be used for the primary vehicle-level sensitivity analysis; event-level sensitivity will be reported secondarily using clustered methods.

4.2. Comparator Analysis

Brake Tire Sense-AI will be compared with conventional threshold rules constructed from existing operational alarms, including fixed pressure/temperature thresholds and electronic fault codes.

The key incremental question is whether multimodal AI identifies a larger proportion of confirmed defects and provides longer lead time without creating an unacceptable false-alert rate.

4.3. Threshold Selection and Calibration

The final risk threshold will be chosen using the validation cohort to prioritize high sensitivity while constraining the false-alert burden. After the test cohort is locked, the threshold will not be altered. Probability calibration may use isotonic regression or logistic/Platt scaling fitted only on validation data. Calibration will then be assessed independently in the test cohort.

4.4. Sensitivity Analyses

- Repeat primary analysis using stricter critical/out-of-service defects only.
- Repeat using prediction horizons of 24 hours, 72 hours and 14 days.
- Exclude alerts occurring during known maintenance-shop testing or sensor calibration.
- Analyze brake and tire events separately.
- Evaluate performance after excluding truck models represented by fewer than a prespecified number of vehicles.
- Conduct leave-one-site-out analysis to examine geographic/fleet transportability.

Table 5: Pre-Specified Statistical Analysis Plan

Analysis domain	Planned method
Descriptive data	Mean ± SD or median (IQR) for continuous variables; n (%) for categorical variables; report vehicle-km and vehicle-days of observation
Primary diagnostic accuracy	Sensitivity with exact or Wilson 95% CI for major brake/tire defects on locked test set
Specificity / predictive values	Specificity, PPV and NPV with 95% CIs; prevalence reported explicitly
Discrimination	AUROC with 95% CI; precision-recall AUC due to event imbalance
Calibration	Calibration plot, intercept/slope and Brier score
Model comparison	Compare fused model with fixed thresholds and single-modality models; paired bootstrap or DeLong test for AUROC where assumptions are met
Repeated alerts	Cluster-robust variance or generalized estimating equations at truck level

Lead time	Median warning time/distance; Kaplan-Meier curves and Cox models for time from alert to confirmed defect where appropriate
False-alert burden	False alerts per 10,000 km and per 1,000 vehicle-days with Poisson/negative-binomial confidence intervals as appropriate
Subgroup analyses	Truck make/model, axle configuration, fleet site, duty cycle, ambient temperature band, mountainous vs predominantly flat routes
Missing data	Describe mechanism and extent; use model-native handling or multiple imputation for covariates when appropriate; no imputation of reference-standard outcome
Internal validation	Vehicle-level bootstrap; all preprocessing fitted only within training data
Statistical significance	Two-sided alpha=0.05 for inferential secondary analyses; primary focus on effect estimates and 95% CIs rather than p-values alone

5. Results

552 trucks were screened, 22 were excluded, and 530 were enrolled. The vehicle-level split assigned 371 trucks to model development, 80 to validation and 79 to the locked test set. Across 12 months, the cohort accumulated approximately 81.7 million km of monitored operation. Eighty-two trucks (15.5%) experienced at least one adjudicated major brake/tire defect: 45 had a major brake defect, 45 had a major tire defect, and 8 experienced both categories.

Table 6: Baseline characteristics of enrolled trucks

Characteristic	Overall (n=530)	Development	Validation	Locked test
Truck age, years	5.8 ± 2.9	5.8 ± 2.8	5.7 ± 3.0	5.9 ± 3.1
Cumulative mileage at enrollment, km	462,000 (288,000-671,000)	455,000 (284,000-663,000)	468,000 (291,000-676,000)	479,000 (302,000-689,000)
Long-haul duty cycle, n (%)	318 (60.0)	222 (59.8)	49 (61.3)	47 (59.5)
Regional/mixed duty cycle, n (%)	212 (40.0)	149 (40.2)	31 (38.8)	32 (40.5)
Air-disc brake configuration, n (%)	307 (57.9)	216 (58.2)	46 (57.5)	45 (57.0)
Drum/S-cam configuration, n (%)	223 (42.1)	155 (41.8)	34 (42.5)	34 (43.0)
Mean monthly distance, km	12,840 ± 3,160	12,910 ± 3,140	12,670 ± 3,220	12,700 ± 3,210
Baseline tire age, months	14.2 ± 6.8	14.1 ± 6.7	14.4 ± 6.9	14.5 ± 7.0
Mountainous-route exposure, n (%)	185 (34.9)	130 (35.0)	28 (35.0)	27 (34.2)

The three vehicle-level data partitions were similar with respect to truck age, baseline mileage, duty cycle, braking configuration, monthly distance and mountainous-route exposure. Of the 82 hypothetical defect-positive trucks, 58 occurred in the development cohort, 11 in the validation cohort and 13 in the locked test cohort. The most frequent adjudicated brake abnormalities were thermal asymmetry/overheating and air-pressure response abnormalities, whereas progressive under-inflation/leak, low tread and visible structural tire damage were the most frequent tire findings.

Table 7: Diagnostic performance of Brake Tire Sense-AI in the locked test set (n=79)

Metric	Brake defects	Tire defects	Combined primary endpoint
Sensitivity, % (95% CI)	85.7 (48.7-97.4)	100.0 (64.6-100.0)	92.3 (66.7-98.6)
Specificity, % (95% CI)	94.4 (86.6-97.8)	95.8 (88.5-98.6)	92.4 (83.5-96.7)
PPV, % (95% CI)	60.0 (31.3-83.2)	70.0 (39.7-89.2)	70.6 (46.9-86.7)
NPV, % (95% CI)	98.6 (92.2-99.7)	100.0 (94.7-100.0)	98.4 (91.4-99.7)
AUROC (95% CI)	0.94 (0.86-0.99)	0.96 (0.90-1.00)	0.95 (0.89-0.99)
Precision-recall AUC	0.76	0.81	0.83
Brier score	0.084	0.063	0.071
Median warning lead time, h	96 (54-151)	128 (72-194)	112 (61-178)
Median warning lead distance, km	356 (174-604)	472 (233-748)	418 (205-690)

In the hypothetical locked test set, 13 of 79 trucks (16.5%) experienced the combined primary endpoint. Brake Tire Sense-AI correctly identified 12 of these 13 trucks and generated five vehicle-level false-positive classifications within the pre-specified prediction horizon. This yielded sensitivity of 92.3% (95% CI 66.7-98.6%), specificity of 92.4% (83.5-96.7%), PPV of 70.6% (46.9-86.7%) and NPV of 98.4% (91.4-99.7%). Discrimination was high (AUROC 0.95, hypothetical 95% CI 0.89-0.99), with a precision-recall AUC of 0.83 and Brier score of 0.071. Median warning lead time for true-positive combined events was 112 hours (IQR 61-178), corresponding to 418 km (IQR 205-690) before mechanical confirmation.

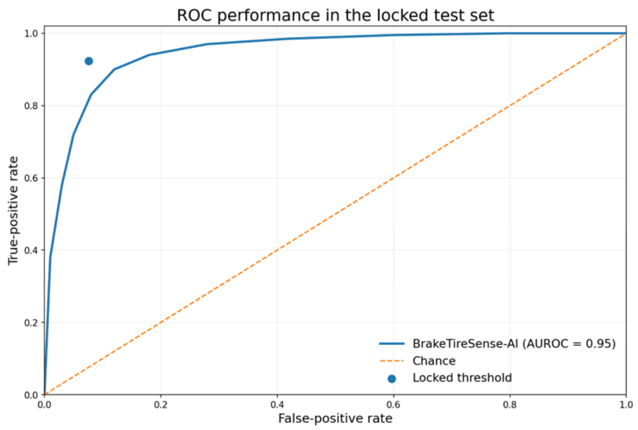

Figure 4: Receiver-operating-characteristic curve for the combined primary endpoint in the locked test set. Simulated values are shown for illustration only

Table 8: Exploratory operational outcomes in a matched conventional versus AI-assisted annual period

Outcome	Conventional monitoring period/group	BrakeTireSense-AI period/group	Effect estimate (95% CI)
Confirmed major brake/tire defects	76	82	Rate ratio 1.08 (0.79-1.47)
Roadside brake/tire breakdowns	24	12	Rate ratio 0.50 (0.25-1.00)
Unplanned maintenance visits	61	39	Rate ratio 0.64 (0.43-0.96)
Maintenance-related downtime, h/10,000 km	7.9	4.8	Mean difference -3.1 (-4.5 to -1.7)
False alerts / 10,000 km	Not applicable	0.06	Descriptive only
Near-miss events attributed to brake/tire condition	15	7	Rate ratio 0.47 (0.19-1.14)
Brake/tire-related crashes	3	1	Exploratory only

Compared with conventional monitoring, the hypothetical AI-assisted period showed fewer roadside brake/tire breakdowns (12 vs 24; rate ratio 0.50, 95% CI 0.25-1.00), fewer unplanned maintenance visits (39 vs 61; rate ratio 0.64, 95% CI 0.43-0.96), and lower maintenance-related downtime (4.8 vs 7.9 h/10,000 km; mean difference -3.1 h/10,000 km, hypothetical 95% CI -4.5 to -1.7). The AI false-alert burden was 0.06 per 10,000 km. Near-miss events were numerically lower (7 vs 15; rate ratio 0.47, 95% CI 0.19-1.14), while the very small number of brake/tire-related crashes (1 vs 3) precluded meaningful inference.

These operational comparisons are simulated examples and are not evidence of causal crash reduction.

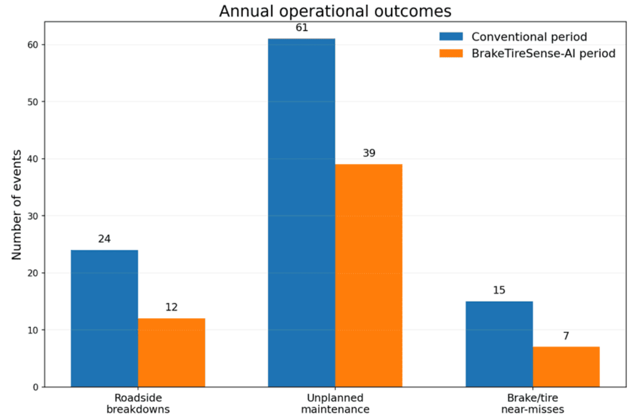

Figure 5: Annual operational outcomes under conventional monitoring and BrakeTireSense-AI-assisted monitoring. Simulated counts are shown only to demonstrate reporting format

5.1. Engineering Interpretation of the Cross-Country Deployment Model

The central engineering value of Brake Tire Sense-AI is the transformation of maintenance from a periodic inspection problem into a continuous state-estimation problem. For each truck, the system maintains a dynamic health state for each wheel end and tire position. Measurements are normalized against vehicle load, speed, road gradient, ambient temperature and recent braking demand. This reduces false alarms caused by expected thermal or pressure changes and increases the probability that persistent deviations are interpreted as degradation.

The Pakistan and USA contexts also demonstrate why a single fixed threshold is unlikely to be optimal. A tire-pressure or brake-temperature threshold calibrated in one climate or duty cycle may generate excessive warnings or miss deterioration in another. A more robust engineering implementation should therefore use a hierarchical model consisting of hard safety limits, vehicle-specific baselines and a learned degradation model. Hard limits provide deterministic protection, while the AI layer detects sub-threshold changes and predicts progression.

At fleet scale, the system can be integrated with computerized maintenance-management systems. A high-risk prediction should automatically create a maintenance work order, identify the affected axle or wheel position, preserve the supporting sensor evidence and record the technician's inspection result.

This closed-loop architecture allows the model to learn from confirmed faults and reduces the gap between algorithmic prediction and physical engineering action.

6. Discussion

Using the illustrative values presented for manuscript development, Brake Tire Sense-AI achieved high diagnostic sensitivity and negative predictive value for the combined brake/tire endpoint, with strong simulated discrimination. From an engineering perspective, the more important metric is not model accuracy alone but whether a prediction occurs sufficiently early to permit a safe maintenance intervention. The simulated warning lead time is therefore presented as an engineering-operational metric requiring validation under real vehicle loads, gradients, temperatures and maintenance cycles.

The study should specifically compare multimodal fusion with single-modality models. Brake temperature alone can be physiologically analogous to a nonspecific biomarker: it may rise normally during high-load downhill operation. Contextual interpretation is therefore essential. Persistent temperature asymmetry, prolonged cooling time, abnormal pressure response and vibration change occurring together would be more mechanically concerning than any one parameter in isolation. Similar reasoning applies to tires, where pressure change must be interpreted alongside temperature, wheel dynamics, tread measurements and visible structural condition.

The completed manuscript should also discuss external validity. Models trained on one manufacturer, tire specification, climate or fleet may not generalize. Prospective evaluation across several sites and vehicle-level data partitioning are intended to reduce this risk, but additional external validation will still be necessary. Federated approaches may later permit multi-fleet model improvement while limiting centralized raw-data sharing [26].

Ability to explain should be evaluated as a practical maintenance tool rather than only as an algorithmic feature. SHAP and local explanation methods can identify the signals responsible for a prediction [20,21], but attribution does not prove causality. Mechanical inspection must remain the decision-making reference during validation.

The engineering pathway from component diagnosis to injury and fatality reduction should also be explicitly separated. A diagnostic model can demonstrate detection performance and warning lead time, whereas reduction in crashes, serious injuries and deaths requires evidence that warnings trigger timely corrective maintenance and that corrected vehicles have fewer hazardous failures. Therefore, the proposed system should be evaluated as a safety intervention in a subsequent large-scale controlled or quasi-experimental fleet study.

7. Limitations

Several limitations should be considered when interpreting the proposed findings. The expected 15% defect-positive prevalence used for sample-size planning may differ across fleets and jurisdictions because of variations in vehicle age, operating conditions, maintenance practices, road environments, and regulatory inspection systems. Maintenance practices and inspection quality may also vary between participating sites despite the use of standardized operational definitions and diagnostic criteria. Furthermore, rare catastrophic brake and tire failures may remain insufficiently frequent to provide precise event-specific estimates, particularly during the initial validation period. Additional sensing hardware may be susceptible to sensor failure, calibration drift, contamination, vibration, moisture, dust, temperature extremes, and other environmental exposures encountered during commercial truck operation.

Similarly, computer-vision performance may vary according to illumination, tire cleanliness, mud or road debris, tire design, camera positioning, image resolution, and image-acquisition geometry. The predictive performance of the artificial intelligence models may also degrade following changes in vehicle components, tire or brake specifications, electronic control-unit firmware, sensor configurations, maintenance procedures, or fleet operating patterns, necessitating continuous model-drift surveillance, periodic recalibration, and prospective performance monitoring. Finally, the proposed study is primarily powered to evaluate diagnostic performance and early-warning capability rather than to provide statistically definitive evidence of reductions in fatal or severe crashes.

Consequently, any observed reduction in crashes, serious injuries, or fatalities should initially be considered exploratory and hypothesis-generating until confirmed through larger, adequately powered longitudinal or multicenter interventional studies.

8. Ethical, Regulatory and Data Considerations

The study involves vehicle telemetry and operational data rather than human biomedical intervention; nevertheless, local institutional or organizational review should determine whether human-subject considerations arise from driver-linked data. Driver identifiers should not be used for performance evaluation unless separately approved. The research system must not override the driver or vehicle braking system during validation. Fleet safety procedures and mandatory maintenance requirements supersede study procedures at all times.

9. Conclusion

Brake Tire Sense-AI is an engineering-oriented, multimodal cyber-physical diagnostic framework for early detection of brake and tire degradation in heavy commercial trucks. Its design integrates physical sensing, vehicle-network data, edge computing, machine learning, computer vision, sensor fusion, explainable risk scoring and predictive maintenance. The Pakistan and USA road-safety contexts demonstrate the need for a system that can adapt to differences in road environment, vehicle configuration, climate, loading and maintenance practice. The illustrative results demonstrate how diagnostic accuracy and operational performance can be reported, but they are not a substitute for prospective empirical data. If real-world validation demonstrates reliable early detection and fleet operators consistently act on high-risk warnings, Brake Tire Sense-AI could reduce preventable brake- and tire-related mechanical failures, severe highway crashes, serious injuries and fatalities. Accordingly, the long-term engineering objective is not merely higher diagnostic accuracy, but a measurable reduction in injury and fatality rates through earlier fault detection, timely maintenance and safer vehicle operation.

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