



Footsteps: A Review of Train Approach, Speed, Direction, and Distance Detection Methods Using Vibrations

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Abstract: Train detection is fundamental to railway signaling and safety, traditionally relying on infrastructure-heavy systems such as track circuits and axle counters. While reliable, these methods involve significant maintenance and are often limited in remote areas. This paper provides a comprehensive review of emerging vibration-based sensing techniques, which utilize accelerometers and geophones to capture distinct vibration signals for determining train presence, speed, direction, and distance. The review evaluates vibration-based approaches by comparing them with other modalities, including vision-based, acoustic, and magnetic detection. Finally, the study identifies current research gaps and outlines future directions for smarter, non-intrusive rail monitoring systems.

Index Terms: Direction detection, Distance estimation, non-intrusive sensing, Railway safety, Speed estimation, Train detection, Vibration sensing.

1. INTRODUCTION

Traditional train detection relies on track circuits and axle counters, which are reliable but require extensive, high-maintenance infrastructure. To improve coverage in remote areas and enable smarter monitoring, research has shifted toward vibration-based sensing using accelerometers and geophones. While early methods used simple thresholding, modern approaches leverage wireless sensor networks and machine learning to analyze rail and ground signatures for real-time data on train presence, speed, direction, and arrival time. This paper reviews these vibration-based advancements while contextualizing them against alternative modalities such as vision, acoustic, and magnetic detection.

2. VIBRATION-BASED TRAIN DETECTION APPROACHES

Vibration sensing utilizes accelerometers or seismometers attached to rails, sleepers, or nearby ground to capture the time-series acceleration and velocity data generated by a train's dynamic

impact. An approaching train is identified by a gradual increase in vibration amplitude and specific frequency patterns, reaching a peak as it passes the sensor [1]. This method offers a low-cost, non-line-of-sight alternative with a long detection range—potentially spanning kilometers—but remains susceptible to ambient noise from traffic or other trains [1], [2]. Consequently, advanced signal processing and machine learning are employed to filter background noise and reliably extract four key parameters: train presence, speed, direction, and distance estimation or time of arrival [2].

A. Train Approach / Presence Detection Using Vibrations

Vibration-based train detection provides a "yes/no" indication of an approaching train by capturing characteristic energy patterns. Early proof-of-concept work by Angrisani et al. (2010) utilized simple accelerometers and thresholding to protect track workers [3]. This research evolved into wireless sensor networks developed by Berlin and Van Laerhoven (2012, 2013), which leveraged on-node processing and "distributed vibration footprints" to achieve over 97% classification accuracy across multiple nodes [4, 5].

Most detection methods exploit the vibration intensity curve, where energy rises to a peak as the train nears the sensor [1]. To overcome varying background noise, Zorbas et al. (2025) introduced an adaptive IoT approach using 3-axis acceleration vector norms to predict time-to-arrival (TTA) 10–15 seconds in advance [1]. Beyond amplitude, frequency-domain analysis—such as the neural networks used by Ardiansyah et al. (2018) and Suharjono et al. (2019)—helps distinguish trains from environmental noise by identifying spectral peaks related to wheel and track resonance [6, 7]. This is further supported by the experimental data compiled by Tao (2023), confirming the baseline stability of wayside vibration parameters [8]. Similarly, deep learning models introduced by Tian et al. (2025) demonstrate that automated signal parsing can isolate approach profiles even in high-speed scenarios [9]. Advanced mathematical methods, like the Hankel matrix ranks (H-ranks) proposed by Orinaite et al. (2025), allow for even earlier detection by identifying subtle structural changes in the signal before the amplitude becomes large [10].

Recent advancements have integrated AI and TinyML, allowing complex models to run on low-power edge devices for real-time inference [2]. These systems not only improve detection robustness but also offer a "dual function" benefit: the same vibration data used for detection can simultaneously monitor structural health, such as identifying loose fasteners or track instability [11, 12]. With detection ranges spanning several kilometers, vibration sensing is a highly viable, cost-effective alternative for both permanent crossing warnings and portable safety devices for maintenance crews [1, 9]. Once a train's presence is confirmed by these systems, analyzing the velocity of the train is the next required step to calculate accurate arrival windows.

B. Train Speed Estimation from Vibrations

Estimating the speed of a train using wayside sensors is valuable for many reasons: it can enhance safety at crossings (by estimating time of arrival), aid in condition monitoring (speed affects track force and vibration), and even allow speed enforcement or diagnostics on lines without onboard speed sensors. Traditionally, train speed is measured by onboard devices (e.g.,

tachometers or GPS) or indirectly by track-side devices like spaced axle counters or Doppler radar.

Vibration-based methods offer an alternative by extracting speed information from the vibration signal itself. There are two primary strategies for vibration-based speed estimation: time-of-flight methods using multiple sensors and signal feature methods using one or more sensors.

Time-of-flight approach: Estimate train speed by placing two or more sensors at a known distance along the track and measuring the time interval between vibration events. Instead of just sticking to traditional cross-correlation, newer systems are leaning into temporal sequence models. For example, Silka et al. (2022) showed that a recurrent neural network (RNN) can naturally learn from time-series vibration data, making it highly effective at tracking complex sequences and predicting high-speed train dynamics over time [13,14]. This approach also inherently determines direction based on the sign of the time lag. Similarly, Berlin et al. (2013) utilized time delays between triggers in a distributed wireless network to compute velocity [5]. While highly accurate and direct, these methods require synchronized sensors and a communication infrastructure between nodes to function effectively.

Signal feature approach: Conversely, speed can be inferred from a single sensor by analyzing how a train's dynamic loading and frequency content shift with velocity. As speed increases, periodic excitations from wheelsets passing rail joints or sleepers occur at higher frequencies, creating a Doppler-like shift in the vibration spectrum [15]. Kouroussis et al. (2015, 2018) demonstrated that ground vibration peaks related to bogie passing frequencies move predictably with speed, allowing for velocity estimation within ~5% accuracy even under varying soil conditions [16, 17, 18]. Similarly, Jurdic et al. (2018) utilized a model-based approach, matching measured vibrations to templates of rail deflection physics to infer velocity [19].

Recent advancements by Wang et al. (2020) have combined time-frequency analysis, such as Wavelet and Short-Time Fourier Transforms (STFT), with known train geometry [20]. By integrating the timing of axle impulses with the physical distance between bogies, they achieved high-precision results with errors as low as 0.6–3%. This demonstrates that standard accelerometers can achieve accuracy comparable to radar guns, providing a versatile solution that works across different track structures without requiring specialized speed-sensing hardware [20].

Machine learning offers a data-driven alternative for speed prediction by training models to map raw or preprocessed vibration signals directly to train velocity, bypassing the need for manual feature derivation. Yildirim, Sevim, and Kalkat (2023) demonstrated this by using three types of artificial neural networks to estimate speeds at level crossings [21]. Their study found that these models could effectively learn the complex relationship between vibration patterns and speed, achieving low mean squared error and promising practical accuracy. A key advantage of this neural network approach is its ability to inherently compensate for variables like differing train types or changing environmental conditions that might complicate traditional physical models [21].

Recent research has further advanced vibration-based speed measurement through deep learning and cross-disciplinary seismic analysis. A preprint by Tian et al. (2025) highlights the use of convolutional neural networks (CNNs) to automate feature extraction from vibration

spectrograms, potentially outperforming manual methods in noisy or high-speed scenarios [9]. At extreme speeds, Krylov (2015) identifies a "ground vibration boom" that occurs as trains approach the velocity of Rayleigh waves, creating unique, high-amplitude signatures that could be exploited for specialized high-speed detection [14]. Furthermore, Rebert et al. (2024) applied geophysical techniques to treat the train as a moving seismic source, using a linear sensor array to invert the wavefield and recover precise kinematics, including subtle speed fluctuations and inter-axle distances [22]. This convergence of transportation and seismology confirms that sophisticated signal processing can decode detailed information about a train's motion from its vibrational footprint.

Controlled experiments, such as those by Carneiro et al. (2026), have refined speed estimation models by measuring ground vibrations at speeds up to 120 km/h, confirming that higher velocities correlate with increased vibration amplitudes and frequency shifts [18]. These empirical studies provide the necessary data to validate algorithms under real-world variability. Collectively, research demonstrates that train speed can be accurately estimated through three distinct vibration-based approaches: time-of-flight methods using sensor pairs for high precision [5, 14], single-sensor methods leveraging spectral and pattern analysis to achieve 1–5% accuracy [13, 15], and machine learning models that handle complex, non-linear environmental effects [20, 23]. The success of these methods indicates that a single set of accelerometers can serve a dual purpose: detecting a train's presence while simultaneously providing the speed data necessary for adaptive, safety-critical warning systems.

Beyond determining speed, the system must establish the train's directional vector, which can be extracted as a direct byproduct of the multi-sensor architectures used for velocity tracking.

C. Train Direction Detection via Vibrations

Determining train direction is vital for signaling systems, such as activating specific warning sequences at level crossings. In vibration-based sensing, this is typically achieved through multi-sensor configurations where the arrival order of signals inherently indicates the direction of travel. In a simple two-sensor setup (Sensors A and B), a train approaching from A's side will trigger sensor A before sensor B, and vice versa. By comparing trigger times or utilizing the cross-correlation methods proposed by Bonavolonta et al. (2015), the sign of the calculated time lag (positive or negative) naturally reveals which sensor was passed first, providing a reliable determination of the train's direction [5, 24].

In vibration-based sensing, determining a train's direction is a reliable byproduct of multi-point sensing. Berlin et al. (2013) demonstrated that a distributed sensor network can function like a series of virtual "track circuits," establishing direction by tracking a train's movement sequentially across a sensor array [5]. This capability is inherently linked to multi-sensor speed estimation; for instance, two sensors spaced a few hundred meters apart can confidently determine direction by comparing synchronized timestamps or utilizing cross-correlation, as shown by Bonavolonta et al. (2015) [24].

Analogous to acoustic methods that use microphone arrays to identify a vehicle's bearing (Rocha

et al., 2021) [25], a pair of vibration sensors "listens" for the arrival order of signals to resolve the train's path [5, 24]. While single-sensor direction detection remains challenging due to site-specific variables like rail impedance, multi-track lines can resolve direction by placing individual sensors on each track. Ultimately, because direction is a straightforward addition to any two-sensor system designed for speed, it remains a highly feasible and critical feature for operational railway warning systems [5, 14, 24, 25].

Combining directional orientation with speed data provides the baseline mathematical parameters required to dynamically track and localize the train's position along the rail corridor.

D. Distance and Location Estimation (Train Position)

Distance detection in vibration-based systems refers to localizing a train or determining its time-to-arrival (TTA). While traditional signaling relies on block occupancy, vibration sensors can quantify distance by leveraging the nonlinear growth of vibration amplitude as a train approaches. Zorbas et al. (2025) developed a model that uses vibration intensity as a proxy for distance, assuming that higher intensity correlates with a closer train [1]. By mapping these intensity levels to a TTA model, their system successfully provided approximately 15 seconds of warning during field tests, detecting trains from several hundred meters to a kilometer away, depending on speed [1]. Although this method may not always provide distance in absolute meters, it offers a reliable estimation of lead time, which is critical for triggering early warning alarms in railway safety applications.

Explicit distance measurement and localization are significantly enhanced by multi-sensor configurations. Berlin et al. (2013) demonstrated that a sequence of sensor activations across an array allows for tracking a train's position over time [5]. Furthermore, while structural monitoring networks can utilize specialized optical fiber arrays to measure localized ground strains [26], a more advanced implementation is Distributed Acoustic Sensing (DAS), where optical fiber cables function as distributed vibration sensing elements. Milne et al. (2020) showed that DAS can monitor up to 40 km of track from a single installation, providing continuous localization with a positional accuracy of 10 meters or better [27].

For point-sensor setups, distance can be calculated by combining speed estimates with the time elapsed since the initial detection. Researchers like Orinaite et al. (2025) have used advanced algorithms, such as H-rank, to forecast a train's arrival time, effectively estimating the "distance-to-go" before the train even reaches the sensor [10]. While single-sensor distance estimation is inherently approximate due to variations in soil attenuation and train types, multi-sensor fusion approaches—such as that proposed by Salim et al. (2025)—improve confidence by providing more spatial data, achieving approximately 95% accuracy in identifying a train's specific track section [15]. In summary, with vibration methods, one typically gets a qualitative distance (train is near or far) unless additional information is used. However, combining vibration sensing with known train speed or multiple sensor triggers can yield a quantitative location. For practical purposes like warning systems, the time-to-arrival prediction is often sufficient and more directly actionable than distance in meters [1]. Nonetheless, as systems like DAS have shown, vibration sensing can evolve

into full train tracking along the line when scaled up spatially [28], [29]. This could complement or back up existing train position tracking in signaling systems, especially in dark territories (non-signaled lines) or during signaling failures. For our scope, the key takeaway is that distance estimation is feasible (especially time-to-arrival forecasting as a form of distance measure) and has been demonstrated in research prototypes, though it may require calibration and sometimes multiple sensors for higher precision. To better understand where vibration-based methods stand relative to alternative technologies, Table 1 provides a comprehensive comparison of different train detection modalities based on their sensing technology, detection range, capabilities, advantages, and limitations.

Table 1: Comparison of Train Detection Modalities

Modality	Sensing Technology	Detection Range	Primary Capabilities	Primary Advantages	Key Limitations
Vibration (Single/Multi)	Accelerometers, Geophones	0.5–5 km	Presence, Speed (1–5% error), Direction (array), TTA	All-weather, long-range warning, non-line-of-sight, dual-use for structural health	Sensitive to ambient noise (traffic); requires site-specific calibration
DAS (Fiber Optic)	Distributed Acoustic Sensing / Optical Fiber	10–40 km	Continuous localization, high-precision speed, and direction	Massive coverage from a single installation; inherently distributed	High infrastructure cost; high power requirements
Vision-Based	Cameras + Deep Learning	50–300m	Identification, obstacle detection, optical speed estimation	Rich data output allows for visual obstacle/train identification	Performance degrades in fog, rain, or darkness; computationally intensive
Acoustic (Airborne)	Microphone Arrays	300–500 m	Speed and direction estimation; horn detection	Low-cost and non-intrusive	Interference from wind/rain; short range due to signal attenuation
Magnetic	GMR or Inductive Sensors	< 5 m	High-precision axle counting, car count, speed/direction	All-weather reliability; unaffected by rust or visibility	No early warning (at-location detection only); very short range
LiDAR / Radar	Optical or RF Reflectors	50–500 m	High-precision range and Doppler speed data	Extremely high accuracy for local tracking	High cost; susceptible to interference from weather and dirt

3. OTHER DETECTION MODALITIES: VISION, ACOUSTIC, MAGNETIC, AND MULTI-SENSOR

While vibrations are a central focus of this review, it is worthwhile to briefly compare other non-track-circuit detection methods that have been explored, as each comes with its own set of advantages and limitations. Some systems even combine multiple modalities to improve reliability [17], [25].

A. *Vision-Based Detection*

Vision-based detection utilizes cameras and computer vision algorithms to identify trains by recognizing their shape, motion, or lights. Yan et al. (2025) demonstrated that deep learning models can effectively detect obstacles and approaching trains in metro tunnels using existing camera footage [28]. While these systems provide rich data, including train identification and precise visual localization, they are computationally intensive and require significant power compared to low-power vibration sensors [2, 28].

A major limitation of vision systems is their reliance on clear line-of-sight and adequate lighting; environmental factors like fog, heavy rain, or darkness can significantly reduce detection range [2, 30]. Consequently, while vision is highly effective for monitoring controlled environments like stations or urban crossings, these reliability issues and power demand often limit its use as a standalone solution for early detection in remote areas [2, 26, 30]. In summary, cameras can provide detailed tracking and distance measurements but remain vulnerable to being "blinded" by the environment, making them better suited as a complementary rather than primary safety-critical detection tool [2].

B. *Acoustic-Based Detection*

Acoustic sensing captures airborne sounds—such as engines, fans, and wheel-rail friction—using microphones to classify train movement. Sato et al. (2018) utilized two-microphone arrays and machine learning to distinguish trains from road vehicles, successfully estimating speed and direction by analyzing arrival time differences between sensors [27, 31]. While non-intrusive and capable of identifying specific frequency patterns like horns, acoustic methods generally have a limited effective range of 300–500 meters due to high-frequency attenuation [25, 31].

A primary challenge for airborne acoustic systems is interference from wind, rain, and ambient noise, which can mask train signatures or trigger false positives. Evaluation by Hellman et al. (2019) noted that while these systems provide near-instantaneous alerts, their short range makes them best suited for localized warning zones, such as blind curves [23]. To improve reliability, some operators explore fusing acoustic data with vibration sensing for redundancy.

Beyond airborne sound, Acoustic Emission (AE) techniques monitor high-frequency elastic waves within the rail material. Yilmazer et al. (2012) demonstrated that AE sensors can isolate structural signatures, such as microscopic crack growth, even amidst high-amplitude rolling noise [32]. Unlike standard microphones, these internal signals are resistant to environmental attenuation from wind or precipitation, providing a robust, low-power solution for concurrent train detection and structural health monitoring in remote environments [32].

C. *Magnetic and Electromagnetic Detection*

Magnetic detection leverages the large metallic mass and electrical systems of trains to sense distortions in the Earth's magnetic field. Zhang, Lee, and Pong (2013) demonstrated that Giant Magneto Resistive (GMR) sensors placed near rails can reliably detect a train's presence and even estimate its speed, length, and car count by analyzing the pattern of magnetic disturbances [33]. Because each steel axle produces a distinct pulse in the sensor output, timing and counting these pulses allows for precise data on train composition—information that traditional track circuits cannot provide [33].

Unlike vision-based or acoustic methods, magnetic sensors are unaffected by weather, visibility, or track surface conditions like rust. They are compact, low-power, and non-intrusive, often mounted directly to rail ties or the rail web without requiring the insulated joints necessary for track circuits. While their effective range is short—typically limited to a few meters—they are ideal for high-precision tasks such as axle counting and can be deployed in arrays to determine speed and direction. In practice, magnetic detection remains a cornerstone of railway operations, with ongoing research focusing on integrating these sensors with wireless modules for easier, more flexible deployment.

D. *Multi-Sensor Fusion and Hybrid Systems*

Radar and LiDAR sensors provide high-precision train detection by measuring reflections or utilizing the Doppler effect for direct speed and range data. Dias et al. (2025) combined LiDAR with GNSS timing to achieve detection at 500 meters, though standalone units often have shorter ranges (dozens to a hundred meters) due to beam divergence and environmental interference [29]. While highly accurate, these technologies are often expensive, power-intensive, and susceptible to degradation from fog, rain, or dirt [27, 34, 35]. To address individual sensor limitations, the industry is shifting toward multi-sensor fusion. Salim et al. (2025) demonstrated that fusing vibration data with gyroscopes or magnetometers can yield a 95% accurate detection system that simultaneously monitors track conditions [15].

Hybrid systems allow for strategic redundancy: for example, using long-range vibration sensors for early warning and magnetic sensors for precise "at-location" confirmation. This approach leverages the strengths of diverse modalities—such as combining acoustic horn detection with seismic vibration—to significantly reduce false alarms and meet the high reliability standards required for railway safety [15, 23]. Ultimately, while traditional track circuits remain the fail-safe standard for signaling, alternative methods excel in specialized niches. Vision provides rich identification data, acoustic sensing is low-cost and non-intrusive, and magnetic sensors (axle counters) offer precise presence detection. Vibration-based detection, however, occupies a "sweet spot" by providing long-range warning, lower power consumption, and all-weather reliability. When enhanced by modern edge computing and smart algorithms, these systems offer a versatile solution for modern rail monitoring and worker safety [1, 17, 27].

Although these alternative modalities demonstrate experimental merit, bridging the gap to viable field deployment requires resolving underlying hardware and architectural limitations.

4. RESEARCH GAPS AND FUTURE DIRECTIONS

A. Advanced Hardware: dsPIC and ESP32 Integration

A critical advancement in the hardware architecture of train detection systems is the integration of a **dsPIC** alongside the **ESP32** to address performance bottlenecks. Past approaches that relied solely on a single ESP32 microcontroller often struggled with timing interrupt jitter and significant data gaps because a single chip had to simultaneously manage high-speed sensing, digital signal processing (FFT), neural network inference, and wireless communication. By offloading computationally intensive tasks like band-pass filtering and Fast Fourier Transforms (FFT) to a dedicated dsPIC, the system ensures high-speed processing without the risk of missing critical data. This dual-core efficiency allows the ESP32 to focus on running lightweight neural networks and managing communication tasks, effectively ensuring that vital vibration signatures are captured even during periods of heavy data transmission.

While optimizing computing hardware addresses real-time throughput, ensuring the long-term operational autonomy of distributed nodes necessitates sustainable field power strategies.

B. Harvesting Energy and Deployment Longevity

For widespread deployment of wireless vibration sensors along tracks, powering them is a practical challenge. Batteries need replacement, which is labor-intensive in the field. Research into energy harvesting from vibrations themselves is quite relevant—if a sensor can scavenge energy from the train vibrations or from solar, it could be self-sustaining. Some studies have looked at piezoelectric harvesters on tracks that generate power from passing trains [2]. Integrating such harvesters with detection sensors is a promising direction so that devices can have a lifespan of years without maintenance. Additionally, ensuring these devices can operate through extreme temperatures, humidity, and so on is an engineering challenge that academia can contribute to by testing robust packaging and low-power firmware designs [2].

Resolving hardware-level power and computing limitations establishes the foundation for scale, which must then be verified through widespread field validation.

C. Standardization and Large-Scale Validation

Most studies to date have been conducted on limited datasets – often a specific track segment with a few dozen train passings [5], [13]. There is a lack of large-scale, multi-site validation of vibration-based detection systems. Future research should focus on extensive field trials, collecting vibration data under diverse conditions (different track structures, train types, weather, etc.) and testing the algorithms' generalizability. This would help develop standardized performance metrics (detection range, probability of detection, false alarm rate) comparable to traditional systems. An initiative to create an open repository of train vibration signals, similar to databases in speech or image recognition, would greatly benefit the community and enable consistent benchmarking of different methods. Currently, as noted by Zorbas et al. (2025), there was practically only one publicly available accelerometer dataset for train detection (“Trainspotting” data from 2012) [1] – a clear indication that more community data-sharing is needed.

Expanding field trials to diverse locations explicitly introduces the problem of environmental interference, requiring more robust noise-filtering methodologies.

D. Noise Robustness and False Alarm Reduction

Sensitivity to environmental noise from highways or construction remains a primary concern (Zhou et al., 2022) [2]. Future work should explore adaptive noise cancellation using reference sensors and multi-axis accelerometers to distinguish longitudinal rail vibrations from vertical ground motion. Redundancy through sensor arrays and machine learning classifiers—trained on diverse false scenarios—is required to make vibration-based systems as fail-safe as traditional track circuits.

In addition to localized structural noise, dynamic seasonal changes demand that algorithms autonomously adapt to shifting baseline conditions.

E. Calibration and Environmental Adaptation

Vibration signal characteristics vary with temperature, which affects rail tension (Zhang et al., 2021) [12] - as well as waterlogged ballast and seasonal soil changes [36]. Future research should investigate self-calibrating algorithms that "learn" background noise during periods with no trains. Models, including Kouroussis' [16] frequency method, must adapt to environmental parameters to maintain accurate speed estimation and detection thresholds.

Minimizing localized environmental errors secures measurement fidelity, but extending the physical reach of the sensing medium is critical to maximizing early warning windows.

F. Extending Detection Range and Early Warning Time

While vibration sensors can detect trains at distances of several kilometers on ideal continuous welded rails, signal damping on jointed tracks often reduces the practical range. To achieve an extra 5–10 seconds of lifesaving warning time, future research should focus on high-sensitivity amplifiers, strategic sensor placement at resonance points, and cascading sensor activation setups—a daisy-chain concept related to DAS fiber optics [27]. Furthermore, speculative multi-modal systems that combine rail vibrations with distant, low-frequency acoustic signals could further maximize detection range and provide the early warning times necessary for track-side personnel safety.

Maximizing early warning potential is ultimately effective only if these edge devices can interface reliably with broader infrastructure networks.

G. Integration with Signaling and Communication

New sensors must interface with existing signaling in a fail-safe manner. Hellman et al. (2019) [23] noted that systems should default to indicating a train if a failure occurs. This requires standardized interfaces—perhaps mimicking axle counter outputs—and cloud computing for system-wide scalability. Using TinyML on microcontrollers to communicate detections over low-power networks like LTE/5G Zhou et al. (2022) [2] is essential for ensuring low-latency, reliable

communication.

Managing interconnected signaling arrays and complex multimodal data streams necessitates shifting toward advanced artificial intelligence frameworks.

H. Advanced Machine Learning and AI

While initial studies introduced neural networks for detection and speed estimation (Zorbas et al., 2025) [1], [6], [20], modern deep learning models like CNNs or LSTMs could significantly improve sensitivity by extracting features beyond handcrafted methods. However, the railway industry requires high explainability; a "black-box" model with 99% accuracy is still concerning if the 1% false scenario remains uninterpretable. Future research should focus on Explainable AI (XAI) and data augmentation to overcome limited real-world data. Utilizing RNNs for vibration time-series prediction, Silka et al. (2022) [22] could detect anomalies—such as unexpected silence—to determine if a train has stopped or if interference occurred. Furthermore, AI-driven multi-sensor fusion, integrating vibration, acoustic, and magnetic inputs via multi-objective optimization (Salim et al., 2025) [15], offers a path toward robust, safety-critical validation.

Implementing explainable deep learning models ultimately equips the system to resolve challenging operational edge cases, including high-velocity dynamics.

I. High-Speed and Specialty Scenarios

High-speed rail (>300 km/h) presents unique vibration challenges [14]. Future research should tailor algorithms for specific environments like tunnels (Yan et al., 2025) [28] and develop systems capable of classifying train types (e.g., freight vs. passenger) based on their specific vibration footprints [5] to enable adaptive timing logic.

Systematizing these hardware, processing, and environmental advancements provides a clear developmental framework for next-generation railway safety.

5. CONCLUSION

In conclusion, vibration-based train detection has matured from conceptual studies into a viable technique that can enhance railway safety systems. It offers a way to detect trains without direct track circuitry, useful in scenarios where conventional methods are impractical or as an added layer of protection. When combined with complementary sensors –cameras watching a crossing, microphones listening for horns, magnetometers confirming train passage – the result could be a robust, multi-layer detection system that dramatically reduces the probability of undetected trains or false alarms. Such improvements are particularly important as rail networks get busier and push for higher speeds, where the margin for error is slim. Continued interdisciplinary research, development, and field validation will be key to realizing these advances. The studies reviewed herein provide a roadmap and motivation for that ongoing work, and we anticipate that in the near future, intelligent sensor networks will play an integral role in railway approach warning and detection systems alongside the legacy track circuits and axle counters, creating a safer and more efficient railway environment for both operators and the public.

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