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A Fault Diagnosis Model for Railway Track Circuits Using Deep Learning

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Abstract: *The railway track circuit is critical for train detection and signaling safety. Conventional diagnosis methods, reliant on manual checks and threshold-based alarms, are inefficient and prone to errors. This paper presents a deep learning model for intelligent fault diagnosis in track circuits. Real-time voltage and current waveforms under various conditions—normal operation, shunt faults, broken rails, and insulation degradation—are collected to form a high-dimensional time-series dataset. A hybrid neural network combining 1D Convolutional Neural Networks and Long Short-Term Memory networks is designed to automatically extract spatiotemporal features from raw signals. The model performs end-to-end diagnosis, identifying both fault type and severity. Validated using field data from a heavy-haul railway, the model achieves an overall classification accuracy of 98.7%, surpassing traditional threshold and Support Vector Machine methods. Notably, it attains a 95.3% recall rate for early-stage insulation degradation, a fault notoriously difficult for conventional approaches to detect. An integrated attention mechanism enhances interpretability by highlighting signal segments most relevant to the fault. This research demonstrates that deep learning offers a viable pathway toward predictive and intelligent maintenance of track circuits, with significant potential to reduce unplanned downtime and strengthen the safety of railway signaling systems.*

Keywords: *track circuit fault diagnosis, deep learning, predictive maintenance, convolutional neural network (CNN), long short-term memory (LSTM)*

1. Introduction

Railway transportation, as a critical artery of the national economy, places paramount importance on the safety and reliability of its operational control systems [1]. The track circuit, a foundational technology in railway signaling, fulfills two essential functions: train occupancy detection and signal transmission. Its working principle involves using the rails as conductors to form an electrical loop. When a train enters a section, its axles shunt the circuit, causing a change in electrical parameters that is detected to determine occupancy [2]. Given its direct exposure to harsh outdoor environments—subject to mechanical stress, temperature fluctuations, moisture, and contamination—the track circuit is susceptible to various faults [3]. Common failures include rail breaks, insulation degradation, poor shunting due to wheel-rail contact issues, and component aging in sending/receiving equipment [4]. Any undetected fault can lead to serious safety incidents, such as false occupancy detection (signaling a clear track as occupied, reducing efficiency) or, more dangerously, false clearance (signaling an occupied track as clear), which may result in catastrophic collisions [5].

Traditional diagnostic approaches rely heavily on scheduled manual inspections and fixed threshold alarms based on electrical parameters like receiving-end voltage [6]. While these methods have historical validity, they exhibit clear limitations in modern, high-density operational environments [7]. Firstly, threshold-based methods struggle with the "gray zone" of early or intermittent faults, where parameter drift may not exceed the alert threshold but already indicates incipient degradation. Secondly, they lack specificity; a voltage drop could indicate a shunt fault, a broken rail, or insulation problems, but the system cannot distinguish between them, requiring manual intervention for root cause analysis [8]. Thirdly, these methods are poorly adaptive to changing environmental conditions; for example, parameter shifts caused by temperature changes may be misinterpreted as faults, leading to false alarms. Therefore, developing an intelligent, automated, and precise fault diagnosis system is an urgent technical need for ensuring railway operational safety and improving maintenance efficiency [9,10].

The rapid advancement of artificial intelligence, particularly deep learning, offers a revolutionary solution to this challenge [11]. Deep learning models excel at automatically learning complex, hierarchical feature representations from raw, high-dimensional data without relying on manual feature

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engineering [12]. For track circuit fault diagnosis, the raw voltage and current signals over time contain rich information about the circuit's health state. Different fault types manifest as unique patterns or "signatures" in these waveforms—a broken rail might cause a complete signal loss, insulation degradation could lead to increased leakage current and waveform distortion, while a poor shunt might show as an intermittent, fluctuating signal [13]. A well-designed deep neural network can learn to recognize these subtle, nonlinear patterns [14].

This paper explores the application of a hybrid deep learning model for the comprehensive fault diagnosis of track circuits. Moving beyond simple binary classification (normal vs. faulty), we aim to achieve fine-grained multi-class fault identification and severity assessment. The core contributions of this work are threefold: first, the construction of a large-scale, well-annotated dataset of track circuit signals under various health states, filling a gap in publicly available data for this domain; second, the design of a novel neural network architecture that effectively combines local feature extraction and temporal dependency modeling for time-series signal analysis; third, a comprehensive evaluation demonstrating not only high diagnostic accuracy but also the model's capability in early fault detection and providing interpretable results. By transitioning maintenance from a reactive, schedule-based paradigm to a proactive, condition-based one, this technology has the potential to significantly enhance the resilience and economic efficiency of railway infrastructure.

2. Experimental Method

To build and validate a fault diagnosis model for track circuits based on deep learning, this study followed a systematic experimental process that included data collection, preprocessing, model design, and evaluation [15].

The experimental data was sourced from collaboration with the railway infrastructure maintenance department (Table 1). We installed high-precision data recorders at the transmitting and receiving ends of multiple track circuit sections on a busy heavy-haul railway line, collecting end voltage and loop current signals at a frequency of 10 kHz. The data collection process lasted for 18 months, covering the entire seasonal cycle to encompass environmental variables. The raw data collected was labeled by domain experts into multiple categories: normal condition, broken rail failure (simulated by introducing high-resistance connectors), insulation deterioration (gradually reducing ballast resistance), shunting failure (including poor shunting and ideal shunting states caused by track surface contamination), and equipment failure (simulating failure of the transmitting/receiving modules). The final constructed labeled time-series dataset contains over 2000 hours of operational data, from which 500,000 2-second signal segments were extracted, covering different fault types and severity levels [16].

The original signal needs to undergo a preprocessing process before being input into the neural network. Each 2-second segment is first subjected to channel-wise normalization, with its mean set to zero and variance to one, to ensure the stability of the training. To address potential power frequency interference and random noise, a wavelet transform-based noise reduction technique is employed to preserve the key transient features. During the training process, data augmentation techniques are also applied, including random time distortion, amplitude scaling, and the addition of controllable Gaussian noise, to enhance the model's generalization ability.

The core of the model adopts a hybrid architecture named "Temporal-Convolution-LSTM Network" (Table 2). The model takes preprocessed multi-channel time series signals as input. The first stage consists of three parallel one-dimensional convolutional neural network branches, each using a different-sized convolution kernel to extract multi-scale local features [17]. The feature maps output by these branches are concatenated and then undergo channel feature re-calibration through a compression and excitation module. The processed features are sent to a two-layer bidirectional LSTM network to capture the long-term temporal dependencies in the signal. Finally, a temporal attention layer is applied to the LSTM output, enabling the model to focus on the most diagnostic time steps within the signal segments. The final feature vector is processed by a fully connected layer, outputting the probability distribution of the fault category and the regression estimate of the severity [18].

The model is trained using the Adam optimizer, and the loss function is the weighted sum of the classification cross-entropy and the regression mean square error. The dataset is divided into training set, validation set and test set in a ratio of 7:1.5:1.5. During the training process, an early stopping strategy is adopted to prevent overfitting. For comparison, multiple benchmark models were also implemented, including traditional threshold detectors, support vector machines based on manual features, standard one-dimensional CNN and pure LSTM models. All models were strictly evaluated using comprehensive

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indicators on an independent test set.

Table 1. Composition of the Track Circuit Fault Diagnosis Dataset

Fault Category	Description	Simulated Severity Levels	Number of 2-sec Segments	Percentage
Normal	Standard operation under various weather/load conditions.	N/A	105,000	21.0%
Broken Rail	Simulated via introduced high-resistance joints (0.5Ω to 5Ω).	3 levels (Low/Med/High Resistance)	85,000	17.0%
Insulation Degradation	Progressive reduction in ballast resistance (2.0Ω·km to 0.5Ω·km).	4 levels	110,000	22.0%
Shunt Fault	Includes poor shunt (contact resistance 0.1Ω to 0.5Ω) and ideal shunt (0.06Ω).	3 levels	95,000	19.0%
Equipment Failure	Faults in transmitter (output drop) or receiver (sensitivity loss).	2 types	105,000	21.0%
Total			500,000	100%

Table 2. Architecture and Hyperparameters of the Proposed TCL-Net Model

Network Component	Configuration / Hyperparameters	Purpose / Function
Input	Shape: (20000 time steps, 4 channels) [V_send, I_send, V_recv, I_recv]	Raw multi-channel signal.
Parallel 1D-CNN Branches	Kernel Sizes: 3, 5, 7; Filters: 64 each; Activation: ReLU	Multi-scale local feature extraction.
Squeeze-and-Excitation Block	Reduction ratio: 16	Adaptive channel-wise feature recalibration.
Bidirectional LSTM	2 layers, 128 units per direction, dropout=0.3	Capturing long-term temporal dependencies.
Temporal Attention Layer	Attention units: 64	Highlighting diagnostically critical time steps.
Output Layers	1. Classification: Softmax (5 fault classes + normal). 2. Regression: Linear (1 unit per severity-quantified fault).	Multi-task learning for type and severity.
Training	Optimizer: Adam; Initial LR: 0.001; Batch Size: 64; Loss: Weighted (Cross-Entropy + 0.1*MSE)	Optimizing model parameters.

3. Results

The experimental results provide a comprehensive and compelling demonstration of the proposed TCL-Net model's superior diagnostic capabilities compared to conventional and alternative machine learning approaches. When evaluated on the completely unseen test set, which contained complex and noisy signal patterns reflective of real-world conditions, the TCL-Net achieved an overall fault classification accuracy of 98.7%. This performance starkly outperformed all benchmark models. The traditional threshold-based method, which triggered an alarm when the received voltage fell outside a predefined safe range, achieved a mere 76.2% accuracy. Its shortcomings were evident in its high false positive rate—often mistaking normal diurnal variations for faults—and its inability to distinguish between fault types, categorizing everything simply as "faulty." The Support Vector Machine model, utilizing a set of 20 handcrafted time and frequency domain features, reached an accuracy of 89.5%. While a significant improvement over the threshold method, it plateaued due to the inherent limitations of manual feature engineering; the pre-defined features failed to capture the subtle, nonlinear patterns characteristic of early-stage or compound faults. The standard 1D-CNN model achieved 94.1% accuracy, validating the power of automatic feature learning from raw signals. However, its purely convolutional nature limited its ability to model long-range temporal relationships. The LSTM-only model performed slightly better at 95.8% (Table 3), excelling in temporal modeling but lacking in efficient local feature extraction. The TCL-Net's hybrid architecture successfully combined the strengths of both, hence delivering the highest performance.

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A more granular analysis of the classification performance is revealed through the detailed per-class metrics presented in the confusion matrix and derived statistics (Table 4). The model exhibited near-perfect performance in identifying "Normal" states and "Broken Rail" faults, with precision and recall rates exceeding 99.5%. This high reliability for clear-cut faults is crucial for safety. For "Shunt Faults," the model achieved an average precision of 97.8%. Notably, it could reliably differentiate between an "ideal shunt" (a healthy train occupying the track) and a "poor shunt" (caused by wheel-rail contamination), a distinction that is operationally vital but challenging for traditional methods. The most diagnostically challenging category proved to be "Insulation Degradation," especially in its early stages where the change in ballast resistance is minimal. Even here, the TCL-Net demonstrated remarkable efficacy, achieving an overall recall of 95.3% for this class. When analyzing by severity level, the model's recall for "Level-1" (incipient) insulation degradation was 91.5%, dropping only slightly from its near-perfect performance on severe cases. This capability for early detection is a key advantage, enabling proactive maintenance before the fault escalates to a level that impacts operations.

Table 3. Overall Diagnostic Performance Comparison of Different Models

Model / Method	Overall Accuracy (%)	Average Precision	Average Recall	F1-Score	False Positive Rate (%)
Threshold-Based	76.2	0.74	0.71	0.72	18.5
SVM (Handcrafted Features)	89.5	0.88	0.87	0.87	7.2
1D-CNN	94.1	0.93	0.92	0.92	4.1
LSTM-only	95.8	0.95	0.94	0.94	2.9
Proposed TCL-Net	98.7	0.986	0.985	0.985	0.9

Table 4. Detailed Per-Class Performance Metrics for the TCL-Net Model

Fault Class	Precision	Recall	F1-Score	Support (Test Samples)
Normal	0.994	0.997	0.995	15,750
Broken Rail	0.996	0.995	0.995	12,750
Insulation Degradation	0.980	0.953	0.966	16,500
Shunt Fault	0.978	0.988	0.983	14,250
Equipment Failure	0.983	0.992	0.987	15,750

Beyond mere classification, the model's regression branch provided valuable quantitative assessments of fault severity. For insulation degradation faults, the model's predicted ballast resistance values showed a strong correlation ($R^2 = 0.94$) with the actual simulated values. Similarly, for shunt faults, the estimated shunt resistance closely matched the true values (Table 5). This quantitative output transforms the system from a simple alarm generator into a diagnostic tool that can inform maintenance teams about the urgency and nature of the required intervention.

The integrated attention mechanism yielded another significant result: interpretability. By visualizing the attention weights over the input signal sequence for specific fault predictions, we could identify which portions of the 2-second waveform the model deemed most critical. For instance, for a shunt fault, the model consistently attended to the sharp voltage drop transient at the moment of shunting. For early insulation degradation, it focused on subtle low-frequency modulations in the current signal. These visual explanations build trust with domain experts and can potentially help refine human understanding of fault signatures.

Table 5. Fault Severity Estimation Performance (Regression Task)

Fault Type	Severity Metric	Mean Absolute Error (MAE)	R-Squared (R^2)	Example: True vs. Predicted (Typical Case)
Insulation Degradation	Ballast Resistance (Ω·km)	0.08 Ω·km	0.94	True: 1.2 Ω·km; Predicted: 1.14 Ω·km
Shunt Fault	Shunt Resistance (Ω)	0.007 Ω	0.97	True: 0.15 Ω; Predicted: 0.143 Ω
Broken Rail (Joint Resistance)	Joint Resistance (Ω)	0.15 Ω	0.91	True: 3.0 Ω; Predicted: 3.18 Ω

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4. Discussion

The exceptional performance of the proposed TCL-Net model, as evidenced by the quantitative results, unequivocally demonstrates the transformative potential of deep learning methodologies in the domain of railway infrastructure health monitoring. However, these encouraging outcomes necessitate a more nuanced and critical examination that extends beyond mere performance metrics to consider the broader implications, inherent limitations, and practical challenges associated with real-world deployment. The transition from a successful research prototype to a reliable, certified component within a safety-critical signaling ecosystem is a complex journey that involves addressing multifaceted technical, operational, and regulatory considerations.

A foundational aspect of the model's success lies in the quality, diversity, and representativeness of the training dataset. While our dataset, comprising over 500,000 annotated segments from a heavy-haul line, is substantial, it inherently reflects the operational characteristics and failure modes of a specific track circuit technology under particular environmental and load conditions. The railway industry employs a variety of track circuit types, including audio-frequency, jointless, and high-frequency variants, each with distinct operational principles and signal characteristics. The electrical signatures of a seemingly identical fault—such as insulation degradation—may manifest differently in an audio-frequency track circuit compared to the DC or low-frequency AC circuit studied here. Consequently, the direct application of the TCL-Net model to these disparate systems without adaptation may yield suboptimal performance. This underscores the critical importance of domain adaptation and transfer learning strategies for building generalizable diagnostic systems. Future efforts could focus on developing a core, pre-trained feature extractor on multi-domain data, which can then be efficiently fine-tuned with a smaller, site-specific dataset for a new circuit type. This approach would accelerate deployment and mitigate the significant cost of collecting and labeling vast amounts of fault data for every new application. It also highlights an industry-wide need for collaborative frameworks to create shared, anonymized, and well-documented benchmark datasets, which are currently a significant bottleneck in advancing AI applications in rail engineering.

The model's demonstrated prowess in detecting incipient insulation degradation represents a paradigm shift in maintenance philosophy. Traditional threshold-based systems are blind to gradual parametric drifts until they cross a critical, often arbitrarily set, boundary. By contrast, the TCL-Net model identifies subtle, nonlinear patterns in the raw waveform that correlate with early-stage deterioration. This capability enables a transition from reactive or preventive maintenance to genuinely predictive maintenance. Engineering teams can be alerted to a track section with declining ballast resistance months before it would cause a failure, allowing for intervention during a planned maintenance window. This not only prevents service-disrupting failures but also allows for more cost-effective interventions, such as targeted ballast cleaning or drainage improvement, rather than emergency replacements. The quantitative severity estimation provided by the model's regression output further empowers asset managers. By converting a diagnostic alert into a quantifiable metric (e.g., "Ballast resistance has degraded to 1.0 $\Omega\cdot$km with a predicted time-to-failure of 6 months under current trends"), it facilitates data-driven decision-making for prioritizing maintenance activities across a vast network, optimizing the allocation of labor and financial resources. The economic and operational advantages of minimizing unplanned downtime and extending asset life through such predictive capability are profound.

The integration of the temporal attention mechanism addresses one of the most persistent criticisms of deep learning models in safety-critical industries: their opacity as "black boxes." For a diagnostic system to be trusted and adopted within the rigorous safety culture of railways, it must provide some degree of explainability. The attention weights offer a post-hoc interpretation, visually indicating which specific segments of the 2-second signal window were most influential in arriving at a diagnosis. For instance, if the model diagnoses a "poor shunt" and the attention map highlights the initial transient of the voltage drop and a subsequent oscillatory tail, a domain expert can correlate this with the known physics of a high-resistance shunt. This builds a vital bridge between data-driven statistical learning and physics-based domain knowledge. It allows human experts to validate the model's "reasoning," fosters trust, and can even lead to new insights into fault mechanisms. This interpretability feature is not merely a usability enhancement; it is a potential prerequisite for the model's certification under standards like EN 50128 (Software for Railway Control and Protection Systems), which require the verification and validation of safety-related software, including an understanding of its failure modes.

Despite these strengths, significant challenges must be navigated for successful field deployment. The current model operates in a centralized, cloud-based paradigm, which may introduce latency and dependence on communication networks. For real-time or near-real-time diagnostics, especially on lines with limited connectivity, edge computing architectures must be explored. This involves optimizing and compressing the TCL-Net model to run on ruggedized industrial computers at trackside equipment houses, processing data locally and only transmitting alerts and summaries. Another critical challenge is handling "out-of-distribution" scenarios. The model was trained on a closed set of known fault classes. It may behave unpredictably when encountering a completely novel fault, an unprecedented combination of failures, or strong electromagnetic interference from a non-rail source. To ensure system resilience, the diagnostic pipeline should be augmented with an unsupervised anomaly detection module. This module, perhaps based on autoencoders or one-class SVMs, would monitor the reconstruction error or feature density of incoming signals. Signals flagged as highly anomalous, even if not classifiable into a known fault category, would be escalated for urgent human review, ensuring that the system fails safely and alertly.

Finally, the integration pathway into existing operational technology ecosystems must be carefully designed. The diagnostic output—a fault class and severity—must be formatted and communicated in a way that seamlessly integrates with existing Computerized Maintenance Management Systems and control center dashboards. This requires close collaboration with railway operators, signaling engineers, and IT departments to define standardized data interfaces and alert protocols. The ultimate goal is not to replace human expertise but to augment it, providing maintenance teams with a powerful, AI-driven "second opinion" that enhances situational awareness, accelerates root cause analysis, and enables a more strategic, data-informed approach to managing the health of the railway's neural network—the track circuit.

5. Conclusion

This research has successfully developed and validated a deep learning-based fault diagnosis model for railway track circuits, demonstrating a significant leap beyond the capabilities of traditional diagnostic methods. By leveraging a hybrid Temporal-Convolutional-LSTM Network architecture, the model achieves an end-to-end intelligent analysis of raw voltage and current signals, excelling in both the precise classification of fault types—including challenging early-stage insulation degradation—and the quantitative estimation of fault severity. The achieved overall accuracy of 98.7% and the provision of interpretable insights through an attention mechanism present a compelling case for the practical application of this technology.

The implications of this work extend beyond academic interest, pointing toward a tangible evolution in railway maintenance practices. The shift from time-based or threshold-based maintenance to condition-based and predictive maintenance, enabled by such AI models, promises substantial improvements in operational safety, asset availability, and life-cycle cost efficiency. It allows maintenance efforts to be precisely targeted where they are most needed, preventing minor issues from escalating into major failures that disrupt services.

Future work will focus on several key areas to transition from successful prototype to deployed system. This includes testing the model's generalizability across diverse track circuit technologies and railway environments, developing efficient edge-computing implementations for real-time analysis, and integrating the diagnostic outputs directly into computerized maintenance management systems to automate work order generation. Furthermore, exploring semi-supervised or self-supervised learning techniques could reduce the dependency on large volumes of expensively labeled fault data. In conclusion, the integration of deep intelligence into the fundamental elements of railway signaling, as exemplified by this fault diagnosis model, represents a vital step forward in building the smarter, safer, and more resilient railways of the future.

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