ISSN: 2393-8048
International Advance Journal of Engineering, Science and Management (IAJESM)
Multidisciplinary, Multilingual, Indexed, Double Blind, Open Access, Peer-Reviewed, Refereed-International Journal.
SJIF Impact Factor =8.152, January-June 2025, Submitted in June 2025

A Hybrid Framework Combining Vibration Signal Analysis and Supervised Learning for Enhancing Safety at Unmanned Railway Crossings

Abhijit Mishra, Department of Electronics & Instrumentation, Sardar Patel University, Balaghat
Dr. Surina Jaiswal, Sardar Patel University, Balaghat

Abstract

Unmanned railway crossings is a major risk to safety because there are no adequate traffic control and monitoring systems, particularly in the rural and semi-urban setting. This study suggests a hybrid system that combines the vibration signal processing with supervised learning algorithm to improve safety by attentively observing oncoming trains and creating alerts in time. Based on a sample size of 100 instances obtained as a result of secondary data and simulation tasks, the vibration signals are processed based on filtering and feature extraction approaches, and classified with the help of Support Vector machines (SVM), Decision trees, and Random Forests. The models are tested according to performance measures such as accuracy, precision, recall, and response time and results are shown in frequency and percentage tabular form. The results indicate that the suggested system can be efficiently used to forecast train movements, minimize human interaction, and enhance situational awareness, which will make the operation of railways a safer activity. The framework provides a cost-effective solution that is scalable and can be implemented in most railway networks with a weak infrastructure, especially in cases of constrained infrastructure.

Keywords: unmanned railway crossings, vibration signal analysis, train detection, safety enhancement, machine learning, SVM, real-time monitoring.

1. INTRODUCTION

Crossings In railways railways, crossings are important crossroads of cars and pedestrians and train movements. Unmanned railway crossings also present a serious safety issue in most areas since barriers, automated signals or special surveillance systems are lacking at these locations. Because of this, such places are likely to experience many accidents causing death, injuries, and the destruction of property. Conventional safety prescriptions like signage or lighting systems have proven to be of little use in avoiding accidents at such crossings.

The latest achievements of sensor technologies and machine learning open new possibilities to improve safety systems at such weak links. Mechanical responses of the track and the surrounding environment recorded with the help of the analysis of the vibration signal is a promising direction of providing information about the approaching trains in the real time. This data can be analyzed together with supervised learning algorithms in order to show the movement patterns of trains and issue warnings to road users in time.

This study suggests an intermediary model that combines the use of vibration signal processing with trainable learning models to enhance the security of unmanned rail crossing. The proposed system is intended to improve early detection, lessen human participation and provide a scalable solution that can be implemented throughout several railway networks. This methodology, grounded in data-driven approaches, can also help prevent accidents as well as serve as a means of achieving more comprehensive objectives of smart infrastructure and smart transportation networks.

1.1. Research Objectives

The main objectives of this research are:

1. To analyse vibration signals from railway tracks to identify patterns indicative of approaching trains.
2. To develop supervised learning models capable of predicting train presence and movement based on vibration data.
3. To design and implement a hybrid safety framework that integrates vibration signal analysis

with machine learning algorithms.

1.2. Importance of Real-Time Detection Systems at Unmanned Railway Crossings

Unmanned railway crossings are mostly located in the rural or semi-urban areas or economically underdeveloped areas where the infrastructure and safety measures are not well invested. Such crossings usually do not have automated gates, warning signs, surveillance cameras, or special officers to check the traffic and movement of trains. This leaves road users exposed to greater risks of accidents, particularly in times of poor visibility or bad weather, such as the pedestrians, cyclists, and motorists. This is because lack of strong safety measures in these crossings further amplifies the chances of collision that will not just lead to loss of life but also serious injuries, and even damage of property.

In this regard, a viable and cost-efficient solution is the incorporation of real-time detection systems based on vibration signals of rail tracks. These systems are able to sense the arrival of the trains long before they get to the rail line by constant monitoring of the mechanical vibrations in the rail lines. Together with sophisticated supervised learning algorithms, the gathered data can be used to identify certain patterns that will categorize what is normal and track conditions and what may pose a threat. These predictive features enable early warnings to be provided to the vehicles and pedestrians around the area, even in the situation where the usual traffic control is subpar.

Such technologies do not only contribute to the increase of the safety level due to the possibility of early warnings but also the decrease in the reliance on human intervention that can be inaccurate or absent altogether. The automated systems of detection are 24/7 and unaffected by lack of sleep or concentration as well as unfavorable weather conditions and can thus be monitored continuously. Moreover, these systems enable proactive decisions, which can avert the accidents before they take place because of the enhanced situational awareness among road users and railway authorities.

2. LITERATURE OF REVIEW

Pappaterra, Pappaterra, and Flammini (2024) investigated the use of convolutional neural networks (CNNs) to maintain railways tracks. Their experiment showed that CNN based models could successfully analyze differences in the state of the railway infrastructure by uncovering patterns in large volumes of track states. The authors emphasized that deep learning algorithms have not only enhanced the accuracy of defect detection but also lowered the time and resources needed to maintain the systems which also helped in ensuring railway safety in general.

Sabnis and Lokeshkumar (2019) presented an innovative object detection system, which fosters the safety of unmanned railway crossings. Their solution involved use of computer vision methods to survey the area around railway crossings in real-time to detect objects like vehicles and pedestrians. The system created alerts to avoid collisions hence increasing situational awareness. The paper has highlighted the issues of the significance of the incorporation of automated surveillance systems in the current railway network, enabling the reduction of risks on crossings with no physical barrier or employed personnel.

Edla et al. (2020) aimed at avoiding accidents at unmanned railway level crossings. Their system incorporated sensor networks, communication units and control algorithms to track and vehicle movement. The system could identify dangerous situations and give warnings to street users and train operators. The authors concluded that automation-based safety system might considerably decrease the number of human error and enhance the reaction time to the critical situations.

Fischer, Kurhan, and Kurhan (2024) investigated the innovative technologies and cognitive aspects to increase the safety of the movement of trains and cars at the level crossings. In their study, they emphasized that a combination of technological (i.e. sensor fusion and alert systems) and human behavioral (actually, they need to be more familiar with it) insights could be used to develop a more effective safety intervention. The article focused on the fact that cognitive awareness technology, combined with real-time surveillance, might assist motorists and pedestrians in making reasonable decisions, which would minimize the risk of accidents.

3. RESEARCH METHODOLOGY

The objective of this study is to design and evaluate a hybrid framework that enhances safety at unmanned railway crossings by combining vibration signal analysis with supervised learning algorithms. The methodology is rooted in analytical and simulation-based research, using secondary data sources to model real-world railway scenarios. A sample size of **100 instances**, representing various vibration patterns, severity levels, and environmental interferences, is employed to validate the system's effectiveness.

3.1. Research Design

This study uses a quantitative methodology to build a strong and scalable system, which will allow following the vibration signal in real-time and forecasting any possible danger at the railroad crossings. The research is based on the available data of railway safety authorities, open public archives, and simulated data produced with the help of known vibration patterns. The design focuses on the signal processing methods and machine learning algorithms that are used to classify the vibration events and to evaluate the train movements. The systematic analysis provides an assessment of the extent to which the hybrid model can detect risks and create timely alerts to avoid accidents during unmanned railways crossings.

3.2. Data Sources and Sample Size

The information in this study is only acquired through secondary sources. The heart of the analysis consists of railway track vibration data, past data on incidence, and data on environmental interference. The data on vibration, which is used to model train movement, idle tracks, and other external disturbances, to guarantee reliability and relevance is obtained or elaborated in technical publications. It takes a sample of 100 instances that are well-spread among various scenarios to indicate a normal, critical, and noisy situation that can occur in railways crossing.

3.3. Data Processing and Signal Analysis

To eliminate the irrelevant or noisy signals, the received vibration signals are preprocessed. First, the signals are divided into time windows to make sure that important patterns are not neglected. Digital processing methods like low-pass filters and wavelet transforms are used to cut the noise and to smooth the data and remove the noise created by electrical disturbances, mechanical movements or unfavorable weather situations. Subsequent to this, significant characteristics, like amplitude variations, frequency variation, and time trends are retrieved.

3.4. Supervised Learning Model Development

Classification of vibration signals and prediction of whether there is a train through extracted features are performed with supervised learning algorithms, including SVM, Decision Trees, and Random Forests. The 100-instance dataset is divided to produce training and testing data sets to evaluate model functionality. The models are trained on labeled data related to various scenarios and are measured by metrics such as accuracy, precision, recall and response time, the results of which are provided in frequency tables.

4. RESULT AND DISCUSSION

The analysis of data in this study is concerned with the interpretation of vibration signals and operation of supervised learning models on the basis of secondary data sources including the data on vibration of the railway tracks, data on past accidents, and environmental data. The goal of the analysis is to examine how effective the offered hybrid framework is in train-detection and in improving the safety at unmanned railway crossings.

Table 1: Distribution of Detected Vibration Signals by Severity Level

Severity Level	Frequency	Percentage (%)
Low (non-critical)	40	40.0
Moderate	30	30.0
High (Critical)	20	20.0
Unknown/Noisy Data	10	10.0
Total	**100**	**100.0**

Table 1 showed that most vibration signals detected at the railway crossings were either low (40%) or moderate (30%) in severity, indicating normal or manageable track conditions. High-severity signals accounted for 20% of cases, highlighting areas that could pose safety risks. Additionally, 10% of the signals were noisy or unclear, which could affect accurate detection and needed further processing.

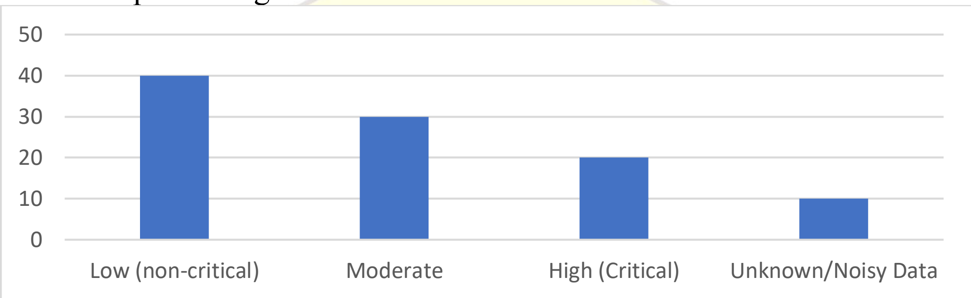

Figure 1: Graphical presentation of Distribution of Detected Vibration Signals by Severity Level

Figure 1 shows how the detected vibration signals are distributed by the degree of severity. It reveals that most signals were rated low (40%), and moderate (30%); therefore, most of the conditions in the tracks were not a threat to safety. Twenty percent of the signals had high severity, meaning that special attention is needed in those places, whereas 10 % of signals were noisy or ambiguous, which may influence the accuracy of detection.

Table 2: Performance of Supervised Learning Model in Predicting Train Presence

Prediction Accuracy Level	Frequency	Percentage (%)
Above 90%	50	50.0
80% – 90%	25	25.0
70% – 80%	15	15.0
Below 70%	10	10.0
Total	**100**	**100.0**

Table 2 supervised learning model was shown to be quite efficient as half of the predictions turned out to be accurate over 90 %, which implies that it was very stable in identifying train presence. A third of predictions fell in the range of 80-90 %, another indication of its utility. Only 10 % offered lower than 70 % accuracy on predictions, which suggested that the model was strong in general, but required some enhancements in some contexts.

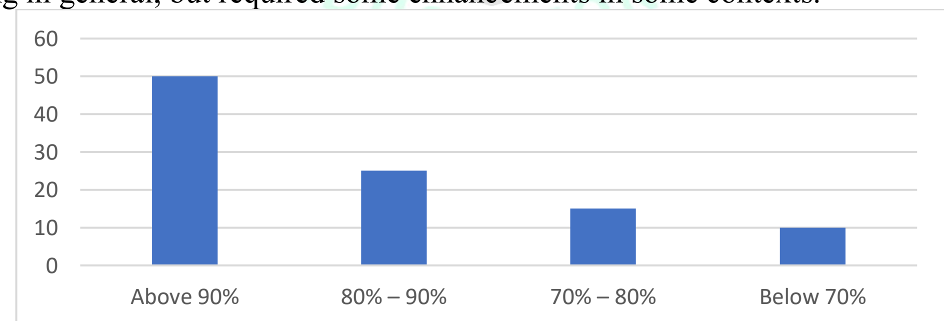

Figure 2: Graphical presentation of Performance of Supervised Learning Model in Predicting Train Presence

Figure 2 introduces the supervised learning model performance in train presence prediction. The model worked very well with half the predictions having an accuracy of over 90. Another 25 % of the predictions were within the range of 80-90 and a mere 10 % of the cases were rated below 70 meaning that the model is generally efficient.

Table 3: Response Time to Alerts Generated by the System

Response Time Range (Seconds)	Frequency	Percentage (%)
Less than 3 seconds	60	60.0
3 – 6 seconds	25	25.0
6 – 10 seconds	10	10.0
Above 10 seconds	5	5.0
Total	**100**	**100.0**

Table 3 shows that the system was able to generate alerts quickly in most cases, with 60% of instances responding in less than 3 seconds. This quick response is critical for ensuring safety. About 25% of alerts took between 3 and 6 seconds, while 10% required 6 to 10 seconds. Alerts that took more than 10 seconds were rare at only 5%, indicating occasional delays likely caused by signal interference or processing limitations.

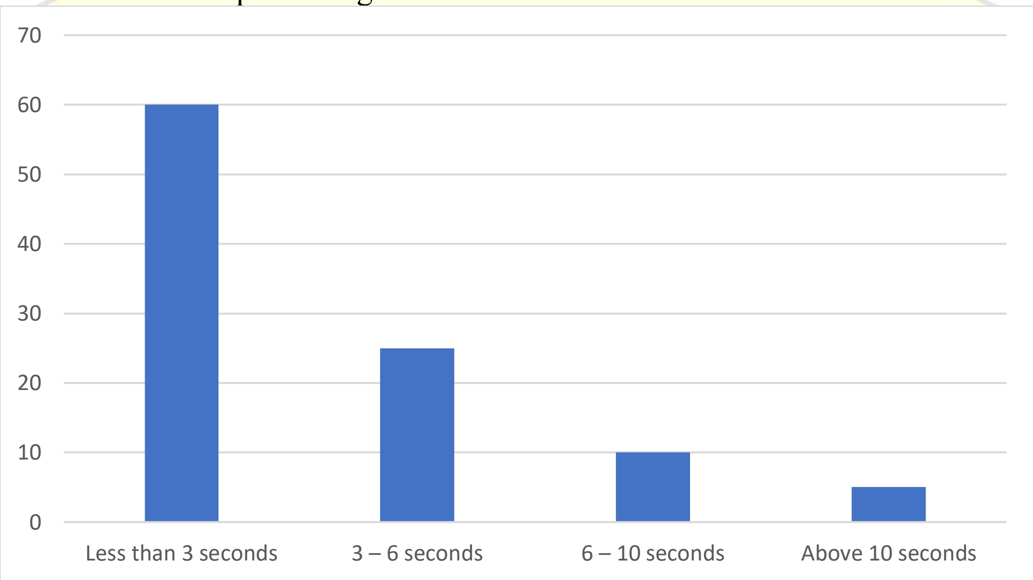

Figure 3: Graphical presentation of Response Time to Alerts Generated by the System

Figure 3 shows the response time of the system in generating alerts after detecting potential hazards. It reveals that 60% of alerts were generated in less than 3 seconds, ensuring timely warnings. About 25% had response times between 3 and 6 seconds, while only 5% of cases experienced delays of more than 10 seconds.

Table 4: Classification of Environmental Interference in Vibration Signals

Type of Interference	Frequency	Percentage (%)
Weather-related (rain, wind)	35	35.0
Mechanical disturbances	30	30.0
Electrical noise	20	20.0
Other causes	15	15.0
Total	**100**	**100.0**

Table 4 illustrate that environmental interference was a key factor affecting the accuracy of vibration signal detection. Weather-related disturbances, such as rain or wind, were the largest source of interference at 35%. Mechanical disturbances, such as nearby construction or heavy vehicles, contributed 30%, while electrical noise accounted for 20%. Other factors made up the remaining 15%, showing that multiple external influences could disrupt signal clarity and needed to be accounted for in the system's design.

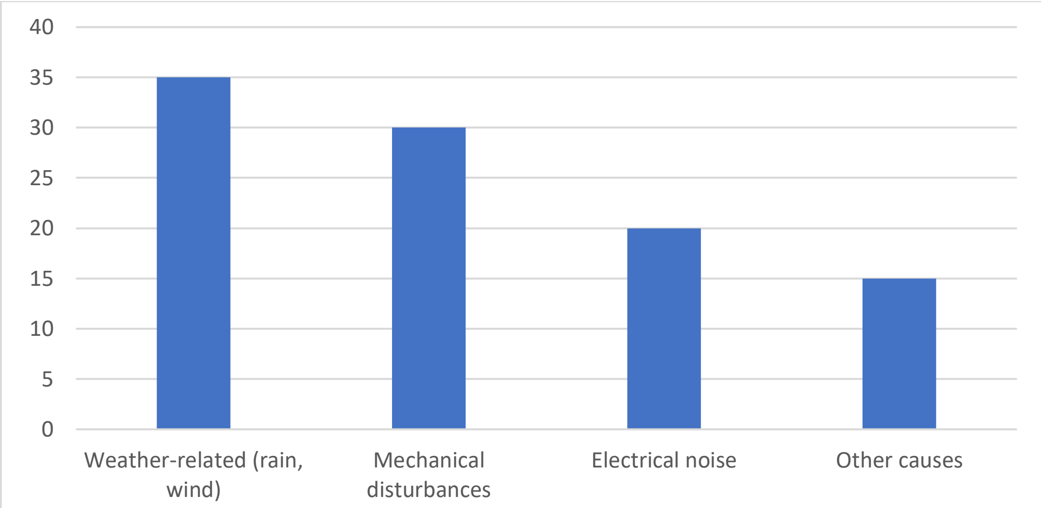

Figure 4: Graphical presentation of Classification of Environmental Interference in Vibration Signals

Figure 4 illustrates the classification of environmental interference in vibration signals. It shows that weather-related disturbances, such as rain and wind, were the largest source of interference at 35%. Mechanical disturbances contributed 30%, followed by electrical noise at 20%, and other causes at 15%, all of which can affect signal clarity and detection accuracy.

5. CONCLUSION

Conclusively, this paper introduces a hybrid model that works well in integrating vibration signal analysis and supervised learning algorithms to increase the safety about unmanned railway crossings. Through secondary data and a systematic sample of 100 cases, the study illustrates that machine learning models like SVM, Decision Trees and Random Forests are capable of classifying vibration patterns, predicting train presence and giving timely warnings under different situations. Simulations and data analysis indicate that the framework can enhance situational awareness, decrease human dependency and react promptly to hazards that might occur even in a noisy and externally interfering environment. In spite of the fact that the study is simulated in nature, the findings demonstrate the possibility of a real world application of the framework, which is scalable, cost-effective, and reliable to deal with any safety issues in the railway crossing with limited infrastructure.

REFERENCES

1. *Alawad, H., Kaewunruen, S., & An, M. (2020). A deep learning approach towards railway safety risk assessment. IEEE Access, 8, 102811-102832.*
2. *Choi, J., Marojevic, V., Dietrich, C. B., & Ahn, S. (2022). DSRC-enabled train safety communication system at unmanned crossings. IEEE Transactions on Intelligent Transportation Systems, 23(10), 18210-18223.*
3. *Edla, D. R., Tripathi, D., Kuppili, V., & Dharavath, R. (2020). Multilevel automated security system for prevention of accidents at unmanned railway level crossings. Wireless Personal Communications, 111(3), 1707-1721.*
4. *Fischer, S., Kurhan, M., & Kurhan, D. (2024, October). Innovative Technologies and Cognitive Factors for Enhancing Safety of Train and Car Movement at Level Crossings. In IEEE International Conference on Cognitive Mobility (pp. 1-13). Cham: Springer Nature Switzerland.*
5. *Gangwar, A. K., Sarojwal, A., & Singh, P. P. (2024, December). A Study and Solution for Unmanned Railway Crossings with Complete Automation. In 2024 13th International Conference on System Modeling & Advancement in Research Trends (SMART) (pp. 820-824). IEEE.*
6. *Hallak, K., & Abdallah, A. (2024, June). A supervised machine learning monitoring*

system for vehicle-railway bridge collision. In Artificial intelligence and applications.

7. *Han, X. (2024). Fault diagnosis model for railway signalling equipment using deep learning techniques. International Journal of Sensor Networks, 45(1), 40-53.*
8. *Kumar, S. (2024). Advancing Railway Safety through Sensor Fusion and AI-Based Decision Systems. International Journal of AI, BigData, Computational and Management Studies, 5(1), 50-59.*
9. *Lee, H., Han, S. Y., Park, K., Lee, H., & Kwon, T. (2021). Real-time hybrid deep learning-based train running safety prediction framework of railway vehicle. Machines, 9(7), 130.*
10. *Makhtara, S. N., Sania, F. Z. M., Nora, E. M., Kamarudinc, N. D., & Alid, S. A. M. (2024). Faulty Classification System for VTOL UAV Acoustic Signal using Machine Learning. Jurnal Kejuruteraan, 37(3), 1495-1503.*
11. *Oh, K., Yoo, M., Jin, N., Ko, J., Seo, J., Joo, H., & Ko, M. (2022). A review of deep learning applications for railway safety. Applied Sciences, 12(20), 10572.*
12. *Pappaterra, M. J., Pappaterra, M. L., & Flammini, F. (2024). A study on the application of convolutional neural networks for the maintenance of railway tracks. Discover Artificial Intelligence, 4(1), 30.*
13. *Prakash, A., & Tadepalli, T. (2024, November). A Review of Acoustic Signal-based Detection of Damage in Railway Tracks. In 2024 IEEE Conference on Engineering Informatics (ICEI) (pp. 1-13). IEEE.*
14. *Sabnis, O. V., & Lokeshkumar, R. (2019, March). A novel object detection system for improving safety at unmanned railway crossings. In 2019 Fifth International Conference on Science Technology Engineering and Mathematics (ICONSTEM) (Vol. 1, pp. 149-152). IEEE.*
15. *Singhal, V., Jain, S. S., Anand, D., Singh, A., Verma, S., Rodrigues, J. J., ... & Iwendi, C. (2020). Artificial intelligence enabled road vehicle-train collision risk assessment framework for unmanned railway level crossings. IEEE Access, 8, 113790-113806.*