

# Intelligent Railway Crossing Safety Systems Using Computer Vision, Sensor Fusion, and Machine Learning: A Review

Gorade Pranita Bhimaji<sup>1</sup>, Bangar Abhishek Popat<sup>2</sup>, Bhosale Sachin Bajirao<sup>3</sup>

<sup>123</sup>Department of Computer Engineering / Jaihind College of Engineering / SPPU, Pune, India

**Abstract** — Railway level crossings remain among the highest-risk elements of the railway system because their safety depends on the behaviour of drivers, pedestrians and cyclists, while conventional protection based on train detection, barriers, warning lights and inductive loops cannot confirm that the crossing area is clear before a train arrives. This paper presents a structured narrative review of 22 verified sources published between 2015 and 2026, including two labelled preprints, organised into seven themes: crossing risk and road-user behaviour; camera based deep learning; trespass and near-miss video analytics; LiDAR, laser and radar sensing; sensor fusion, adverse weather and datasets; machine learning (ML) for crash-risk and injury severity prediction; and warning and edge deployment. Convolutional neural networks and YOLO-type detectors achieve high reported precision for occupancy and road-user detection, LiDAR and laser systems detect small obstacles on low-power edge hardware, camera–radar fusion with redundant voting is the most frequently recommended architecture, and ML models outperform count regression for crash prediction. However, evidence is dominated by singlesite and fair-weather studies, public multi-sensor crossing datasets are scarce, and missed-detection rates, latency and safety integrity are rarely reported. The paper contributes a thematic synthesis, a comparison of fourteen representative studies, a proposed conceptual seven-layer architecture and a prioritised research agenda.

**Keywords**— Level Crossing Safety; Computer Vision; Sensor Fusion; Deep Learning; Obstacle Detection; Machine Learning; Edge Computing

## I. INTRODUCTION

Level crossings are widely regarded as the largest single source of risk on many railway networks. European data for 2015–2016 recorded 469 level-crossing accidents with 288 fatalities and 264 injuries, and level-crossing deaths account for just under 28 % of all railway fatalities [1]. Britain has more than 6,000 level crossings and has averaged about nine deaths per year at them, excluding suicides [2]. The problem is more severe where crossings are unprotected: in Kazakhstan, about 740 of 1,042 crossings are unguarded, and roughly 80 % of railway accident victims are associated with unprotected sites [3].

Most collisions result from road-user error or deliberate violation rather than railway equipment failure. In an on-road study of passive, stop-controlled rural crossings, drivers stopped completely at only 59 % of encounters and violated the stop control at 14 %, and violators made fewer visual checks for trains [4]. Conventional protection, in turn, signals that a train is approaching but does not verify automatically that the crossing area is clear, and inductive loops cannot detect non-metallic obstacles such as pedestrians [1]. Automated obstacle

detection could therefore improve safety, reduce reliance on human operators and shorten road closure times [2], [5].

This review aims to (i) synthesise sensing and learning approaches for level-crossing safety, (ii) compare their methods, performance and limitations, (iii) propose a literature-grounded conceptual architecture, and (iv) identify research gaps that must be closed before deployment.

## II. REVIEW METHODOLOGY

Publisher platforms (MDPI, IEEE, Springer, Elsevier, SAGE, Taylor & Francis, ASME), DOAJ, institutional repositories and arXiv were searched with terms combining level crossing, grade crossing and railway crossing with obstacle detection, computer vision, deep learning, YOLO, LiDAR, radar, sensor fusion, trespass, near miss, crash prediction, injury severity and connected vehicle. Publications from 2021–2026 were prioritised, while earlier studies were retained where they established a method or dataset still in use.

Studies were included when they addressed level or grade crossings directly or provided closely related railway perception methods or datasets. Each record was verified against a publisher page, DOI record or repository; two arXiv

preprints are labelled, and theses, trade articles and unconfirmed records were excluded. Because Scopus and Web of Science searches could not be logged, the review is structured and narrative rather than systematic.

### III. LITERATURE REVIEW

#### 1. Level-Crossing Risk and Road-User Behaviour

Fayyaz et al. reviewed technological developments for level-crossing interlocking and argued that crossings are high-risk because their safety depends on unpredictable road and footpath users [1]. Comparing radar, LiDAR, CCTV, inductive loops, thermal and ultrasonic sensors, they concluded that no single technology suffices: radar cannot classify objects, LiDAR is costly and sensitive to dirt and water, cameras need adequate light, loops miss non-metallic objects and thermal cameras miss inert objects. Dent and Marinov examined the case for automated obstacle detection on British crossings and identified benefits for safety, operator cost and road-user waiting time [2].

Behavioural evidence explains why detection alone is insufficient: in 66 encounters with passive rural crossings, Beanland et al. observed 27 % rolling stops and 14 % violations, and violators checked less for trains [4]. Sansyzbay et al. analysed Kazakhstan's network, where most crossings are unguarded and driver violations cause several deaths each year, and proposed an AI and machine-vision protection system whose benefits are, so far, supported only by calculations [3].

#### 2. Camera-Based Deep Learning for Obstacle Detection

Fayyaz and Johnson compared hand-built CNNs with transfer-learning classifiers for pedestrians, cyclists and vehicles and reported 88 % validation accuracy for MobileNet, against 41.75 % for a conventional neural network trained from scratch [6]. They proposed radar as a second channel in a two-out-of-two (2oo2) interlocking decision. Training images came mainly from public datasets and detection precision and recall were not reported.

Pamuła and Pamuła reframed the task as safe-passage classification: the region between the barriers was divided into image patches that a small three-layer CNN classified as empty or occupied, giving  $F1 = 0.96$  and outperforming an autoencoder and a bag-of-features SVM on 1,000 frames from one crossing [7]. The fixed grid ignores perspective, and all frames came from one site. Carletti et al. ran deep detectors directly on smart cameras and added a barrier-state network so that people and vehicles are only reported as hazards when the crossing is closed, achieving precision of 0.98 and recall of 0.88

on 52 public crossing videos [8]. A preprint combining an ensemble of three YOLOv5 models with a U-Net train-segmentation model on a Raspberry Pi reported 96 % precision and 98 % intersection-over-union [9], and Sansyzbay et al. specify YOLOv8 with ByteTrack tracking alongside microwave sensors and loops [3]. Across these studies, recall is consistently lower than precision, which matters because missed obstacles are the safety-critical error.

#### 3. Video Analytics for Trespass and Near-Miss Events

Aminmansour et al. detected vehicles in near-miss events from train-mounted cameras using region proposals classified by a CNN, improving recall by 29 % relative to deformable part models and R-CNN [10]. Zaman et al. developed a real-time trespass-detection framework for existing surveillance cameras that classifies violators and sends video alerts, tested briefly on three live feeds including one grade crossing [11]. Zhang et al. extended this approach to archival data, processing more than 1,600 h of video at one New Jersey grade crossing and detecting about 3,000 trespassing events for human-factors analysis [12]. Such systems support monitoring and enforcement but are not yet integrated with real-time protection.

#### 4. LiDAR, Laser and Radar Sensing

Amaral et al. used tilting 2D laser scanners to build dense 3D point clouds, learned a background model of the crossing and flagged occupied space that differed from it, detecting obstacles as small as rocks near the rail on 41 point clouds from an operational one-lane crossing [13]. Wisultschew et al. processed a 16-channel 3D LiDAR on a lowpower embedded edge platform that detected and tracked objects in real time and sent warnings to approaching trains, although validation used a road emulating a crossing [14].

Addabbo et al. proposed a standards-based design roadmap for radar crossing surveillance that minimises misdetection when barriers close, using an FMCW radar case study [15]. Radar or LiDAR can also measure train speed and acceleration: Zawodny et al. showed in microsimulation that such measurement could reduce worst-case closure time from 172 s to 54 s at a single simulated site [5].

#### 5. Sensor Fusion, Adverse Weather and Datasets

Because each sensor fails in different conditions, fusion is widely recommended. Fayyaz et al. proposed CCTV–radar fusion with a CNN on the video stream, so that radar maintains detection in fog or heavy rain while the camera provides classification [1]. A 2026 survey of obstacle detection at crossings in adverse weather groups fusion into data-, feature- and decision-level architectures and identifies weather-resilient

datasets, adaptive fusion and real-time pipelines as priorities [16]. Evidence from adjacent onboard railway perception is consistent: Ristić-Durrant et al. report that LiDAR and ultrasonic sensors are limited in heavy rain, standard cameras fail at night and in tunnels, thermal cameras lose contrast at high ambient temperatures, and long braking distances demand long-range detection [17].

Data availability is a major constraint: the main public rail-scene dataset, RailSem19, lacks obstacle annotations [17]. OSDaR23 adds synchronised RGB and infrared cameras, LiDAR, radar and positioning data with 204,091 annotations in 20 classes, but it is recorded from a train rather than from fixed crossing installations [18]. No public, multi-sensor, multi-weather dataset recorded at operating level crossings was identified.

#### 6. Machine Learning for Crash-Risk and Severity Prediction

At network level, ML supports the prioritisation of crossing upgrades. Using 807 validated highway–rail crossings, Senkondo et al. found that random forest, XGBoost, elastic-net, Transformer–CNN and autoencoder–MLP models all predicted crash frequency more accurately than negative binomial regression, with traffic volume, truck share and number of lanes as the most influential predictors according to SHAP analysis [19]. Ren et al. applied XGBoost and SHAP to injury severity in recent federal crash data, identifying older drivers, driving around the gate and trucks among the main risk factors (93.36 % accuracy for the fatal-outcome model) [20]. Farooq and Khattak showed that inventory errors matter: field validation of 560 Nebraska crossings corrected 2,241 values and added

1,732 missing values, and predicted crash frequencies changed by more than 140 % at some sites [21].

#### 7. Warning, Communication and Edge Deployment

Landry et al. evaluated candidate in-vehicle auditory alerts for passive crossings and designed a simulator study of driver compliance, highlighting message content, timing and habituation as design factors [22]. On the infrastructure side, embedded inference on smart cameras [8] and LiDAR edge platforms [14] keeps decisions local, which reduces latency and preserves protection when connectivity fails. Sansyzybay et al. target railway safety standards up to SIL 4 with a redundant controller [3], but no reviewed perception system has demonstrated such certification.

#### 8. Synthesis

Three patterns emerge. The field has moved from operator-supervised CCTV towards on-device deep learning and LiDAR edge processing [8], [14]; nearly all detection studies are validated at one site, on emulated sites or on public videos, rarely in adverse weather or at night [7], [16]; and real-time protection, behaviour analytics and networklevel risk modelling remain separate, although trespass and near-miss data [11], [12] could inform crash-risk models [19], [20].

### IV. COMPARATIVE ANALYSIS

Table 1 compares fourteen representative primary studies. Reported metrics are not directly comparable because tasks, datasets, class definitions and evaluation protocols differ.

Table 1. Comparison of representative intelligent level-crossing safety studies.

| Author, year                  | Objective                              | Method / technology                          | Major reported findings               | Limitations                     |
|-------------------------------|----------------------------------------|----------------------------------------------|---------------------------------------|---------------------------------|
| Aminmansour et al., 2015 [10] | Near-miss vehicle detection            | Train-mounted camera; region proposals + CNN | Recall 29 % higher than DPM and R-CNN | Absolute recall not in abstract |
| Amaral et al., 2016 [13]      | Small-obstacle detection               | Tilting 2D laser scanners; background model  | Obstacles detected in 3D point clouds | 41 point clouds; one crossing   |
| Beanland et al., 2017 [4]     | Driver compliance at passive crossings | Instrumented vehicle; 22 drivers             | 14 % violations; fewer train checks   | No trains present; one region   |
| Zaman et al., 2019 [11]       | Real-time trespass detection           | Deep-learning video analytics; alerts        | No errors reported in tested hours    | Short evaluation; 3 feeds       |

|                               |                                   |                                          |                                             |                                       |
|-------------------------------|-----------------------------------|------------------------------------------|---------------------------------------------|---------------------------------------|
| Fayyaz & Johnson, 2020 [6]    | Classify crossing objects         | CCTV; transfer learning; 2oo2 with radar | MobileNet 88 % validation accuracy          | Public images; no mAP; radar untested |
| Pamuła & Pamuła, 2021 [7]     | Safe-passage classification       | Patch-wise CNN on fixed CCTV             | F1 = 0.96                                   | 1,000 frames; one site                |
| Wisultschew et al., 2021 [14] | Edge detection and tracking       | 16-channel 3D LiDAR; edge IoT            | Real-time tracking, train warnings          | Emulated crossing site                |
| Zhang et al., 2022 [12]       | Trespass analytics                | Deep-learning video analysis             | ≈ 3,000 events in 1,600 h                   | One grade crossing                    |
| Zawodny et al., 2023 [5]      | Shorten closure time              | Radar/LiDAR train-speed measurement      | Closure 172 s → 54 s (simulated)            | Single site; simulation only          |
| Farooq & Khattak, 2023 [21]   | Inventory data quality            | Field validation; FRA model; ZINB        | Predictions changed by >140 % at some sites | 560 crossings; one state              |
| Ren et al., 2024 [20]         | Injury-severity factors           | XGBoost + SHAP on FRA data               | 93.36 % accuracy (fatal model)              | Two years of data                     |
| Carletti et al., 2025 [8]     | People and vehicle detection      | Smart cameras; barrier-state DNN         | Precision 0.98, recall 0.88                 | 52 public videos                      |
| Senkondo et al., 2025 [19]    | Crash-frequency prediction        | RF, XGBoost, Transformer– CNN vs NB      | ML outperformed NB; SHAP drivers            | 807 crossings; one state              |
| Sansyzbay et al., 2026 [3]    | National protection system design | YOLOv8 + ByteTrack; microwave, loops     | Architecture and SIL targets                | Calculations only; no field data      |

## V. PROPOSED CONCEPTUAL ARCHITECTURE

Fig. 1 presents a proposed conceptual architecture derived from the reviewed literature; it has not been implemented or validated.

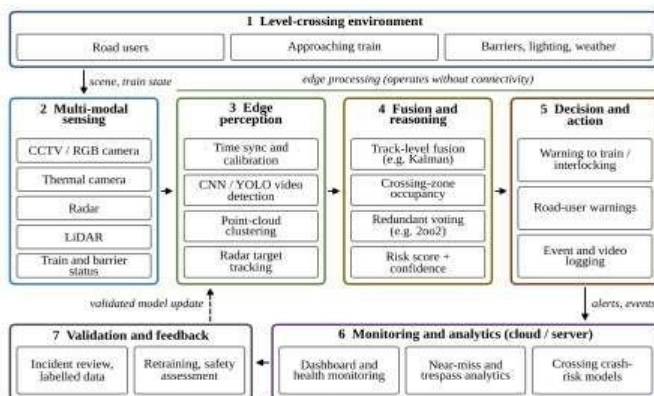


Fig. 1. Proposed conceptual architecture for an intelligent level-crossing safety system (conceptual, not experimentally validated).

Layer 1 is the crossing environment, and layer 2 combines CCTV, thermal, radar and LiDAR sensing with train-detection and barrierstatus inputs, reflecting the complementary strengths identified in the literature [1], [16], [17].

Layer 3 performs edge perception with CNN or YOLO detectors on video [7], [8], point-cloud clustering [13], [14] and radar tracking. Layer 4 fuses detections, estimates zone occupancy and applies redundant voting such as 2oo2 [6] to produce a risk score with confidence, using barrier state to suppress alarms when the crossing is open [8].

Layer 5 warns the train, interlocking and road users, including in-vehicle alerts [22]. Layers 3–5 run at the edge so that protection continues without connectivity and should follow railway safety standards [3], [15].

Layer 6 supports monitoring, trespass analytics [11], [12] and crash-risk modelling on validated inventory data [19], [21]. Layer 7 reviews incidents and retrains models, releasing them to the edge only after independent safety assessment; public datasets can support pre-training [17], [18], but site-specific data remain necessary.

## VI. RESEARCH GAPS AND FUTURE DIRECTIONS

Table 2 summarises the gaps supported by the reviewed evidence and the corresponding research directions.

Table 2. Research gaps and future directions.

| Gap supported by evidence                            | Supporting studies  | Future direction                                          |
|------------------------------------------------------|---------------------|-----------------------------------------------------------|
| Single-site or emulated validation                   | [7], [14], [8], [5] | Multi-site field trials at operating crossings            |
| Limited adverse-weather and night testing            | [1], [17], [16]     | Weather-resilient fusion with thermal and radar channels  |
| No public multi-sensor crossing dataset              | [17], [18]          | Open, synchronised camera–radar–LiDAR crossing datasets   |
| Fusion proposed but not field-validated              | [6], [1]            | Prototype fusion with measured miss and false-alarm rates |
| Recall, latency and safety integrity rarely reported | [8], [15], [3]      | Standard metrics and safety-case evidence                 |
| Analytics and protection developed separately        | [11], [12], [19]    | Link near-miss data to crash-risk models                  |
| Prediction limited by inventory data quality         | [21], [20]          | Automated, validated crossing inventories                 |

Directions still requiring investigation include interlocking integration under railway safety standards, human-factors studies of driver responses to automated and in-vehicle warnings [4], [22], and cost–benefit analysis for retrofitting passive crossings [2], [3].

## VII. CONCLUSION

Intelligent level-crossing safety research has progressed from operator-supervised CCTV to embedded deep-learning detection, LiDAR and laser systems, radar safety designs, camera–radar fusion concepts and ML crash-risk prediction. Precision is high for specific tasks, but evidence is dominated by single-site, fair-weather studies, public crossing datasets are lacking, and missed detections, latency and safety integrity are seldom reported. Reliable deployment will require fusion

validated at operating crossings, transparent safety metrics, interlocking integration and independently validated model updates, as reflected in the proposed architecture.

## REFERENCES

- Fayyaz, M.A.B., Alexoulis-Chrysovergis, A.C., Southgate, M.J., Johnson, C. “A review of the technological developments for interlocking at level crossing”. *Proc. Inst. Mech. Eng. F: J. Rail Rapid Transit* 235(4), 529–539 (2021). <https://doi.org/10.1177/0954409720941726>
- Dent, M., Marinov, M. “Introducing automated obstacle detection to British level crossings”. In: Fraszczyk, A., Marinov, M. (eds.) *Sustainable Rail Transport: Proceedings of RailNewcastle 2017, Lecture Notes in Mobility*, pp. 37–80. Springer, Cham (2019). [https://doi.org/10.1007/978-3-319-78544-8\\_3](https://doi.org/10.1007/978-3-319-78544-8_3)
- Sansyzybay, K., Bakhtiyarova, Y., Turgambay, Y., Tasbolatova, L., Kismanova, A., Zhumagul, A. “Rationale for the development of an intelligent digital level crossing protection system based on AI and machine vision: A safety analysis of railway crossings in the Republic of Kazakhstan”. *Automation* 7(3), 71 (2026). <https://doi.org/10.3390/automation7030071>
- Beanland, V., Salmon, P.M., Filtress, A.J., Lenné, M.G., Stanton, N.A. “To stop or not to stop: Contrasting compliant and non-compliant driver behaviour at rural rail level crossings”. *Accid. Anal. Prev.* 108, 209–219 (2017). <https://doi.org/10.1016/j.aap.2017.09.004>
- Zawodny, M., Kruszyna, M., Szczepanek, W.K., Korzeń, M. “A new form of train detection as a solution to improve level crossing closing time”. *Sensors* 23(14), 6619 (2023). <https://doi.org/10.3390/s23146619>
- Fayyaz, M.A.B., Johnson, C. “Object detection at level crossing using deep learning”. *Micromachines* 11(12), 1055 (2020). <https://doi.org/10.3390/mi11121055>
- Pamuła, T., Pamuła, W. “Detection of safe passage for trains at rail level crossings using deep learning”. *Sensors* 21(18), 6281 (2021). <https://doi.org/10.3390/s21186281>
- Carletti, V., Greco, A., Saggese, A., Vento, B. “Improving safety through advanced obstacle detection at railway level crossings”. *J. Ambient Intell. Humaniz. Comput.* 16(8), 895–904 (2025). <https://doi.org/10.1007/s12652-025-04987-z>
- Amin, A., Chimba, D., Hasan, K., Samson, E. “Intelligent railroad grade crossing: Leveraging semantic segmentation and object detection for enhanced safety”. *arXiv:2403.11060 [cs.CV]* (2024). Preprint, not peer reviewed. <https://doi.org/10.48550/arXiv.2403.11060>

10. Aminmansour, S., Maire, F., Larue, G.S., Wullems, C. "Improving near-miss event detection rate at railway level crossings". In: 2015 Int. Conf. Digital Image Computing: Techniques and Applications (DICTA), pp. 1–8. IEEE, Adelaide (2015). <https://doi.org/10.1109/DICTA.2015.7371273>
11. Zaman, A., Ren, B., Liu, X. "Artificial intelligence-aided automated detection of railroad trespassing". *Transp. Res. Rec.* 2673(7), 25–37 (2019). <https://doi.org/10.1177/0361198119846468>
12. Zhang, Z., Zaman, A., Xu, J., Liu, X. "Artificial intelligence-aided railroad trespassing detection and data analytics: Methodology and a case study". *Accid. Anal. Prev.* 168, 106594 (2022). <https://doi.org/10.1016/j.aap.2022.106594>
13. Amaral, V., Marques, F., Lourenço, A., Barata, J., Santana, P. "Laser-based obstacle detection at railway level crossings". *J. Sensors* 2016, 1719230 (2016). <https://doi.org/10.1155/2016/1719230>
14. Wisultschew, C., Mujica, G., Lanza-Gutierrez, J.M., Portilla, J. "3D-LIDAR based object detection and tracking on the edge of IoT for railway level crossing". *IEEE Access* 9, 35718–35729 (2021). <https://doi.org/10.1109/ACCESS.2021.3062220>
15. Addabbo, T., Fort, A., Della Giovampaola, C., Mugnaini, M., Toccafondi, A., Vignoli, V. "On the safety design of radar based railway level crossing surveillance systems". *Acta IMEKO* 5(4), 64–72 (2016). [https://doi.org/10.21014/acta\\_imeko.v5i4.419](https://doi.org/10.21014/acta_imeko.v5i4.419)
16. Yan, C., Bengtsson, M. "Obstacle detection at level crossings under adverse weather conditions: A survey". *arXiv:2602.01974 [eess.SP]* (2026). Preprint, not peer reviewed. <https://doi.org/10.48550/arXiv.2602.01974>
17. Ristić-Durrant, D., Franke, M., Michels, K. "A review of vision-based on-board obstacle detection and distance estimation in railways". *Sensors* 21(10), 3452 (2021). <https://doi.org/10.3390/s21103452>
18. Tagiew, R., Köppel, M., Schwalbe, K., Denzler, P., Neumaier, P., Klockau, T., Boekhoff, M., Klasek, P., Tilly, R. "OSDaR23: Open sensor data for rail 2023". In: *Proc. Int. Conf. Robotics and Automation Engineering (ICRAE)*. IEEE (2023). <https://doi.org/10.1109/ICRAE59816.2023.10458449>
19. Senkondo, E., Chimba, D., Madalo, M., Yeboah, A., Blue, S. "Comparative analysis of machine learning and statistical models for railroad-highway grade crossing safety". *Vehicles* 7(4), 163 (2025). <https://doi.org/10.3390/vehicles7040163>
20. Ren, Q., Xu, M., Zhou, B., Chung, S.-H. "Traffic safety assessment and injury severity analysis for undivided two-way highway-rail grade crossings". *Mathematics* 12(4), 519 (2024). <https://doi.org/10.3390/math12040519>
21. Farooq, M.U., Khattak, A.J. "Investigating highway-rail grade crossing inventory data quality's role in crash model estimation and crash prediction". *Appl. Sci.* 13(20), 11537 (2023). <https://doi.org/10.3390/app132011537>
22. , S., Jeon, M., Lautala, P.T., Nelson, D. "Getting active with passive crossings: Investigating the use of in-vehicle auditory alerts for highway-rail grade crossings". In: *Proc. 2016 Joint Rail Conference*, pp. 19–26. ASME (2016). <https://doi.org/10.1115/JRC2016-5827>