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AI in Accident Prediction: A Review of Crash Risk Modelling, Spatio-Temporal Deep Learning and Dashcam Accident Anticipation

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Abstract—Road traffic crashes kill more than a million people each year, and India records one of the highest numbers of road deaths in the world. Predicting where, when and how accidents are likely to occur allows authorities to deploy enforcement and engineering measures, and allows vehicles to warn drivers before a collision. This paper reviews artificial intelligence for accident prediction at two scales. At the network scale, it examines statistical crash-frequency models, machine learning comparisons with traditional regression, and spatio-temporal deep learning that combines historical accidents, traffic, weather, road features and points of interest to estimate accident risk for each region and time. At the vehicle scale, it reviews accident anticipation from dashcam video, in which recurrent and relational models attend to road agents and estimate the probability of an imminent collision several seconds in advance. Datasets, evaluation metrics and explainability methods for identifying risk factors are discussed. A five-layer architecture comprising data sources, data integration, risk modelling, explanation and intervention layers is proposed, together with research gaps, objectives, a comparison of approaches and challenges such as under-reporting, class imbalance, data sharing and false warnings. The review concludes that AI-based accident prediction, linked to concrete interventions, can contribute significantly to road safety.

Index Terms—Accident prediction, road safety, crash risk, ConvLSTM, spatio-temporal deep learning, dashcam, accident anticipation, explainable AI

I. Introduction

The World Health Organization reports that road traffic crashes cause about 1.19 million deaths every year [1]. India alone recorded more than 4.6 lakh road accidents and about 1.68 lakh deaths in 2022 [2]. Many of these crashes occur at known black spots, at predictable times or under identifiable conditions, which suggests that a significant share could be anticipated.

Traditional road-safety analysis uses statistical models of crash frequency for road segments, as reviewed by Lord and Mannering [3]. AI extends this work by learning complex, non-linear relationships from heterogeneous data, and by anticipating collisions in real time from vehicle cameras.

This paper reviews AI methods for accident prediction at network and vehicle scales and proposes an intervention-oriented architecture.

II. Background and Fundamental Concepts

2.1 Scales of Accident Prediction

Fig. 1 distinguishes network-level risk prediction (which places and times are risky), segment-level frequency and severity modelling, and vehicle-level anticipation (is a collision about to happen).

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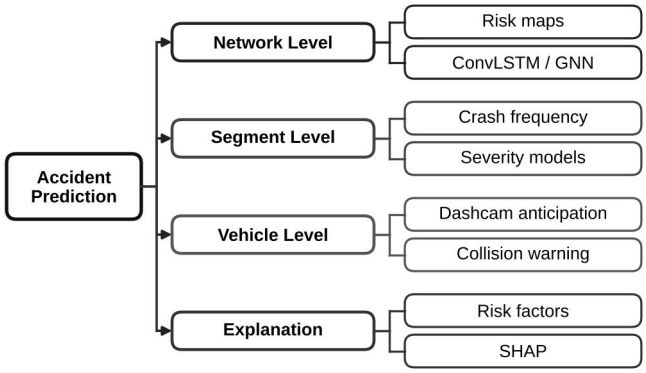


Fig. 1. Scales and methods of AI-based accident prediction.

2.2 Risk Factors

Crash risk depends on traffic volume and speed, road geometry, junctions, lighting, weather, time of day and driver behaviour.

III. Literature Survey

Statistical and early ML models. Lord and Mannering [3] reviewed count models such as Poisson and negative binomial regression for crash frequency and their limitations. Chang [4] compared negative binomial regression with an artificial neural network for freeway accidents and found the neural network competitive without requiring a predefined functional form.

Spatio-temporal deep learning. Yuan *et al.* [5] proposed Hetero-ConvLSTM, which handles spatial heterogeneity across a state using multiple ConvLSTM models [6] over grids of traffic, weather, road and calendar features, and predicted accident counts better than baselines. Moosavi *et al.* [7] built a large countrywide accident dataset from real-time traffic reports and proposed a deep model combining recurrent and embedding components to predict accident risk from sparse data.

Dashcam anticipation. Chan *et al.* [8] introduced a dashcam accident dataset and a dynamic-spatial-attention RNN that predicts accidents about two seconds in advance. Bao *et al.* [9] modelled relations between road agents with graph convolution and estimated uncertainty, improving early and reliable anticipation.

Explanation. SHAP [10] can reveal which factors drive predicted risk, supporting targeted interventions. Table I summarizes these works.

TABLE I Summary of Literature Survey

Ref.	Method	Key Findings	Limitations
[4]	NB regression vs. ANN	ANN competitive for frequency	Single freeway
[3]	Review of crash-frequency models	Method strengths and limits	Statistical focus
[8]	Dashcam DSA-RNN	Anticipation ~2 s ahead	Small dataset
[5]	Hetero-ConvLSTM	Better state-wide prediction	Grid resolution
[7]	Countrywide dataset + DL	Risk from sparse data	U.S. data
[9]	Relational GCN anticipation	Earlier, reliable alarms	Compute cost
[10]	SHAP	Factor attribution	Not causal

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IV. Research Gap

1. Accident data in India are under-reported and lack precise location and time.

2. Accidents are rare, causing severe class imbalance.

3. Models trained in one city or country transfer poorly.

4. Dashcam anticipation models produce false warnings in dense, mixed traffic.

5. Predictions are seldom linked to concrete interventions and evaluated for impact.

4.1 Objectives

1. To review statistical and machine learning crash-frequency models.

2. To examine spatio-temporal deep learning for accident risk prediction.

3. To study vehicle-level accident anticipation from dashcam video.

4. To propose an intervention-oriented accident prediction architecture.

5. To identify challenges and future directions for Indian roads.

4.2 Proposed System Architecture

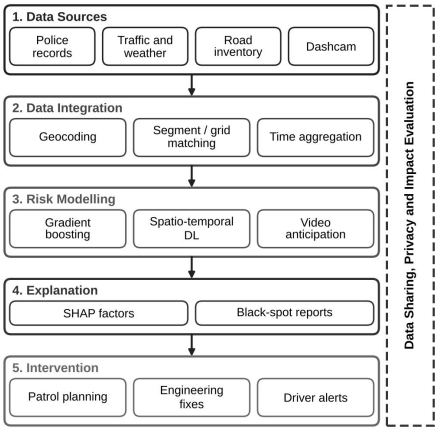


Fig. 2 shows the proposed architecture.

Fig. 2. Proposed five-layer AI-based accident prediction architecture.

4.3 Data Sources Layer

Police accident records, traffic speeds and volumes, weather, road inventory, junction locations, points of interest and dashcam video provide data.

4.4 Data Integration Layer

Records are geocoded, matched to road segments or grid cells and aggregated by time interval.

4.5 Risk Modelling Layer

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Gradient-boosted models and spatio-temporal networks predict accident risk per cell and hour; an in-vehicle model anticipates collisions from video.

4.6 Explanation Layer

SHAP identifies the main factors, such as speed, darkness or rain, for each high-risk location.

4.7 Intervention Layer

Authorities receive risk maps for patrol planning and engineering fixes; drivers receive in-vehicle warnings and navigation alerts for risky zones.

V. Methodology and Working

Fig. 3 describes the workflow. The risk of cell s at time t is predicted as

$$\hat{r}(s, t) = f_\theta(X_{hist}, X_{traffic}, X_{weather}, X_{road}) \quad (1)$$

and trained with a weighted loss that emphasizes rare accident cases. For dashcam anticipation, the frame-level accident probability p_t is compared with a threshold, and the time-to-accident at the first alarm is reported together with average precision.

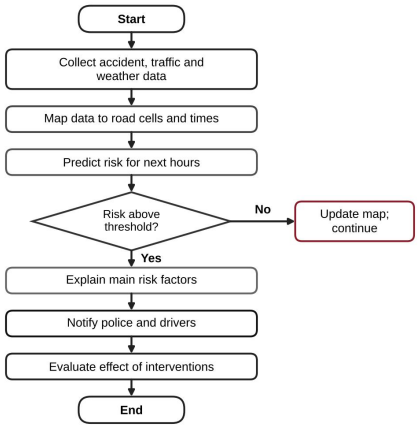


Fig. 3. Accident risk prediction and intervention workflow.

VI. Comparative Analysis

Table II compares approaches. Statistical models are interpretable, machine learning captures non-linear effects, spatio-temporal deep learning uses rich context, and dashcam models act in real time.

TABLE II Comparison of Accident Prediction Approaches

Approach	Data	Interpretability	Time Scale
NB / Poisson regression	Segment counts	High	Years
Gradient boosting	Tabular features	Medium (SHAP)	Hours–days
Spatio-temporal DL	Grids / graphs	Low–Medium	Hours
Dashcam anticipation	Video	Low	Seconds

6.1 Challenges and Future Scope

Table III summarizes challenges. Future directions include integrating accident prediction with emergency response, using connected-vehicle data, predicting accident severity and evaluating interventions with causal methods.

TABLE III Challenges and Mitigation

Challenge	Mitigation
Under-reporting	Combine police, hospital and crowd data
Class imbalance	Weighted loss; resampling
Transferability	Local fine-tuning
False warnings	Uncertainty-aware thresholds
Linking to action	Intervention dashboards; evaluation

VII. Conclusion

AI can predict accident risk across road networks and anticipate collisions from inside vehicles. The reviewed literature shows clear progress from statistical models to spatio-temporal deep learning and relational video models. For Indian roads, better data, handling of rare events and a direct link between predictions and interventions are needed for AI to reduce deaths and injuries.

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References

1. World Health Organization, Global Status Report on Road Safety 2023. Geneva, Switzerland: WHO, 2023.
2. Ministry of Road Transport and Highways, Road Accidents in India 2022. New Delhi: Government of India, 2023.
3. D. Lord and F. Mannering, “The statistical analysis of crash-frequency data: A review and assessment of methodological alternatives,” Transp. Res. Part A, vol. 44, no. 5, pp. 291–305, 2010.
4. L.-Y. Chang, “Analysis of freeway accident frequencies: Negative binomial regression versus artificial neural network,” Saf. Sci., vol. 43, no. 8, pp. 541–557, 2005.
5. Z. Yuan, X. Zhou, and T. Yang, “Hetero-ConvLSTM: A deep learning approach to traffic accident prediction on heterogeneous spatio-temporal data,” in Proc. 24th ACM SIGKDD, 2018, pp. 984–992.
6. X. Shi et al., “Convolutional LSTM network: A machine learning approach for precipitation nowcasting,” in Proc. NeurIPS, 2015, pp. 802–810.
7. S. Moosavi, M. H. Samavatian, S. Parthasarathy, R. Teodorescu, and R. Ramnath, “Accident risk prediction based on heterogeneous sparse data: New dataset and insights,” in Proc. 27th ACM SIGSPATIAL, 2019, pp. 33–42.
8. F.-H. Chan, Y.-T. Chen, Y. Xiang, and M. Sun, “Anticipating accidents in dashcam videos,” in Proc. Asian Conf. Comput. Vis. (ACCV), 2016, pp. 136–153.

[9] W. Bao, Q. Yu, and Y. Kong, “Uncertainty-based traffic accident anticipation with spatio-temporal relational learning,” in Proc. 28th ACM Int. Conf. Multimedia, 2020, pp. 2682–2690.

[10] S. M. Lundberg and S.-I. Lee, “A unified approach to interpreting model predictions,” in Proc. NeurIPS, vol. 30, 2017.