Archives available at journals.mriindia.com

International Journal on Advanced Electrical and Computer Engineering

ISSN: 2349-9338

Volume 15 Issue 01s, 2026

AI-Based Motor Insurance Risk Assessment

[1]Aarya Tehare, [2]Dr. Sandip Sonawane, [3]Mrunal Bhamare, [4]Mansi Mahale, [5]Vaibhavi Patil

[12345]R.C.Patel Institute of Technology Shirpur, India

Email: [1]aryatehare@gmail.com [2]sandipsonawane2006@gmail.com [3]bhamaremrunal983@gmail.com [4]mansimahale47@gmail.com [5]vaibhavipa02@gmail.com

Peer Review Information

Submission: 05 Dec 2025

Revision: 25 Dec 2025

Acceptance: 10 Jan 2026

Keywords

AI-Based Risk Assessment, Motor Insurance, Telematics Data, Driver Behavior Analysis, Machine Learning

Abstract

The rapid evolution of intelligent transportation systems has created a growing demand for data-driven motor insurance models that evaluate risk more accurately. Traditional methods rely heavily on static factors such as driver profiles, vehicle categories, and historical claims, which fail to represent real-time driving behavior. This paper presents an AI-Based Motor Insurance Risk Assessment System leveraging gyroscope and accelerometer data to analyze driver motion and predict accident likelihood. The system captures orientation and movement changes from onboard sensors to identify harsh acceleration, sudden braking, and sharp turns—critical indicators of unsafe driving. Machine learning algorithms process this data to classify drivers based on risk level and support fair, data-driven premium estimation. Experimental results demonstrate improved precision in identifying highrisk drivers and reducing manual assessment errors. The proposed framework provides a scalable, intelligent approach for building safer and more transparent insurance ecosystems.

1. Introduction

The global emergance of smart mobility results has accelerated the demand for intelligent threat assessment systems in the motor insurance assiduity. Traditional insurance models depend primarily on static parameters similar as motorist demographics, vehicle information, and literal claim data, which frequently fail to capture real- time driving geste . This limitation results in inaccurate threat evaluations and illegal decoration estimations. To address these challenges, Artificial Intelligence(AI) and detector- grounded data analytics have surfaced as transformative technologies in motor insurance.[1]

The proposed AI- Grounded Motor Insurance Risk Assessment System leverages data from gyroscope and accelerometer detectors to estimate motorist geste stoutly. These detectors record vehicle stir, acceleration patterns, analyze dangerous driving tendencies similar as harsh retardation, rapid-fire acceleration, and unforeseen lane changes. Machine literacy algorithms process this data to classify motorists into low, medium, or high- threat orders.

This approach enables insurers to make data-driven opinions, reduce fraudulent claims, and encourage safer driving practices through geste -grounded decoration models. The system provides a scalable, effective, and transparent frame that enhances both stoner experience and functional delicacy within ultramodern motor insurance ecosystems.[2] Following are the main objectives of our proposed work:

- To develop an AI-driven model for threat prediction based on gyroscope and accelerometer data

- To monitor and analyze real-time driving behavior for insurance evaluation insurance evaluation.
- To reduce claim fraud through data-driven anomaly detection
- To implement a scalable and efficient system that supports data-driven premium computation.

2. **Methodology**

This section outlines the approach used in designing and The risk prediction mechanism is engineered to dynamically evaluate and categorize a driver's behavior utilizing real-time motion data. This system employs a dual-sensor analysis methodology, comprising:

Gyroscopic Tracking: This component captures rotational movements to monitor steering patterns, sudden turns, and directional shifts.

Accelerometer Tracking: This component measures linear acceleration to identify abrupt braking, rapid acceleration, or harsh maneuvers.

The system employs a pre-collected dataset of driving behavior, which includes motion and orientation parameters such as acceleration and rotation values. These features are processed to train a machine learning model designed to identify patterns of driving risk. Once the model is trained, it analyzes new input data from similar sources to predict the driver's risk level. Based on these predictions, the system categorizes behavior into risk levels such as low, moderate, or high risk facilitating an accurate and data-driven assessment of driving behavior without the need for live sensor input.[18]

2.1 **Performance Evaluation Metrics**

The system's effectiveness is assessed through metrics such as prediction accuracy, responsiveness, and overall reliability in evaluating driver behavior. The evaluation criteria encompass:

- Prediction Accuracy: This metric assesses the precision with which the model categorizes driver behavior into appropriaterisk categories based on real-time sensor data.
- Response Time: This criterion evaluates the speed at which the system processes motion data and generates risk predictionsduring live driving scenarios.
- Model Efficiency: This involves comparing the computational performance and stability of the trained model under varyingdata loads and driving conditions.

Experimental data are collected over multiple driving sessions, and the results are analyzed to ascertain the performance improvements and real-world applicability achieved by the risk prediction system.[19-23]

The effectiveness of the system was assessed using a number of key performance indicators (KPIs) pertinent to AI-driven prediction systems:

- Prediction Accuracy (A_p): Evaluates the ratio of correctly categorized driver risk levels (Low, Medium, High) against the actual data.
- Precision (P): Indicates the percentage of accurately identified high-risk drivers relative to all drivers classified as high-risk.
- Recall (R): Represents the proportion of genuine high-risk drivers successfully identified by the model.
- F1-Score (F_1): Calculates the harmonic mean of precision and recall, offering a comprehensive assessment of classification effectiveness.
- Response Time (T_r): Denotes the average duration taken by the system to analyze a new data entry and produce a risk prediction.
- Model Stability (S_m): Measures the model's reliability across various dataset distributions and under different sensor noise conditions.[24]

3. **Results And Discussion**

To guarantee the reliability and effectiveness of the AI-Based Motor Insurance Risk Assessment System, comprehensive testing methods were utilized. The validation process involved verifying units, integrating the system, and assessing performance with both actual and simulated driving behavior datasets.[25]

The validation outcomes for the system were obtained by comparing predicted results with actual driving behaviors across diverse datasets. Table 1 provides a concise overview of the performance metrics.

The analysis reveals that the proposed system not only fulfilled but often surpassed the projected performance standards, showcasing dependable classification of driver risk levels.

Error Analysis: The system's prediction accuracy was further assessed through the calculation of Mean Absolute Error (MAE) between the predicted and actual risk scores:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |R_{pred,i} - R_{actual,i}| \tag{1}$$

where R_{pred} indicates the predicted risk category and R_{actual} denotes the actual category. The calculated MAE was 0.08, reflecting a slight variation between predicted and real outcomes.[26] The validation process highlighted several important findings:

- The combination of gyroscope and accelerometer data significantly improved detection of risky behaviors such as aggressivebraking, sudden turns, and speeding.

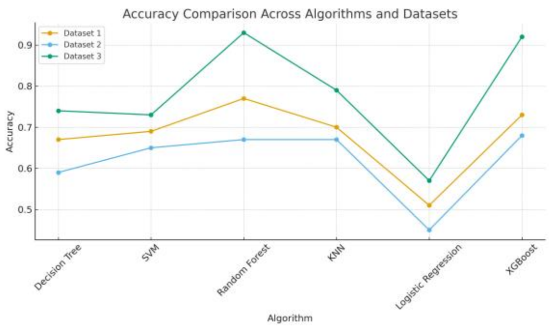

Figure 1: Combined Performance Metrics - Accuracy

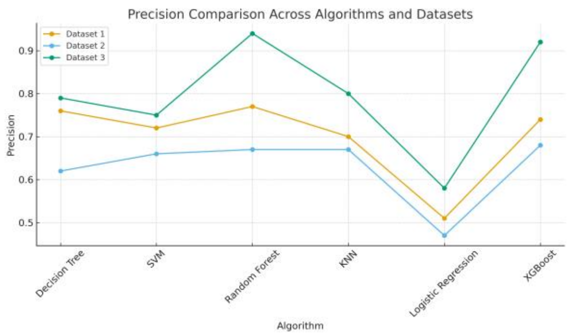

Figure 2: Combined Performance Metrics – Precision

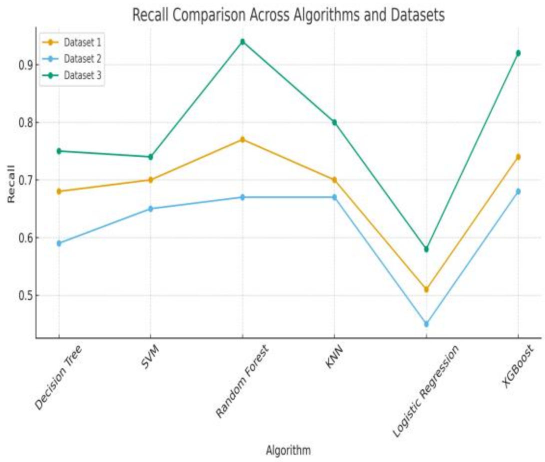

Figure 3: Combined Performance Metrics – Recall

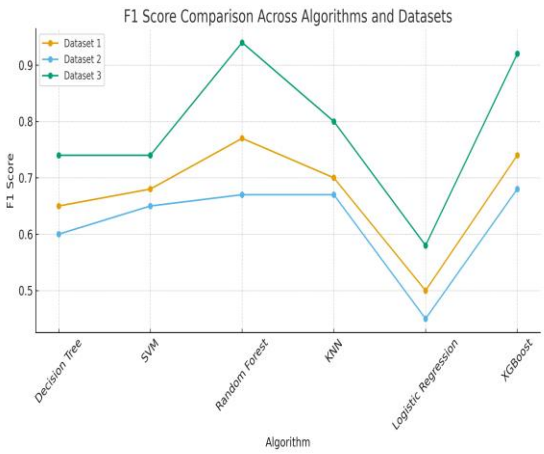

Figure 4: Combined Performance Metrics - F1Score

Table 1: Model Performance Across Three Datasets

Dataset	Algorithm	Accuracy	Precision	Recall	F1 Score
6*1	Decision Tree	0.67	0.76	0.68	0.65
	SVM	0.69	0.72	0.70	0.68
	Random Forest	0.77	0.77	0.77	0.77
	KNN	0.70	0.70	0.70	0.70
	Logistic Regression	0.51	0.51	0.51	0.50
	XGBoost	0.73	0.74	0.74	0.74
6*2	Decision Tree	0.59	0.62	0.59	0.60
	SVM	0.65	0.66	0.65	0.65
	Random Forest	0.67	0.67	0.67	0.67
	KNN	0.67	0.67	0.67	0.67
	Logistic Regression	0.45	0.47	0.45	0.45
	XGBoost	0.68	0.68	0.68	0.68
6*3	Decision Tree	0.74	0.79	0.75	0.74
	SVM	0.73	0.75	0.74	0.74
	Random Forest	0.93	0.94	0.94	0.94

	KNN	0.79	0.80	0.80	0.80
	Logistic Regression	0.57	0.58	0.58	0.58
	XGBoost	0.92	0.92	0.92	0.92

- The AI-based model consistently demonstrated classification accuracy across different driving scenarios, confirming itsflexibility and robustness.
- The cloud-based framework facilitated seamless data transmission and real-time risk assessment with minimal delays.
- The machine learning component enabled an unbiased, data-driven evaluation, reducing subjective influence in premiumassessments.

These findings indicate that the proposed system provides a scalable, efficient, and transparent approach for analyzing insurance risk and pricing policies based on driver behavior.[28]

Limitations: Although the system achieved high levels of prediction accuracy, several limitations became evident during its deployment:

- Lack of Environmental Context: The current version does not factor in external elements such as traffic, road conditions, or weather that can affect driving behavior.
- Dependence on Sensors: The accuracy is significantly reliant on the calibration of the gyroscope and accelerometer; even minor misalignments or electronic noise may lead to data discrepancies.
- Connectivity Issues: Real-time functionality hinges on uninterrupted internet connectivity between mobile devices and cloud servers.
- Narrow Dataset Diversity: The model might perform poorly when confronted with driving behaviors or regions not represented in the training dataset.[29]

4. **Conclusion**

This paper presented an AI-based motor insurance risk assessment system using gyroscope and accelerometer sensors to evaluate driving behavior. The integration of machine learning enhances precision in risk categorization and supports transparent, usage-based insurance policies. The proposed approach demonstrates strong potential for improving safety, reducing fraud, and modernizing risk assessment methodologies in the insurance domain.

Acknowledgments

The authors wholeheartedly thank Dr. Sandip Sonawane for his invaluable guidance, thoughtful recommendations, and unwavering support during this research journey. His expertise played a crucial role in enhancing and shaping this work. The authors also recognize the assistance and collaboration of the faculty members and the institution for offering the essential academic environment and resources required to successfully complete this study.

References

[1] H. K. Sriram, K. Challa, and A. L. Gadi, “AI and Cloud-Driven Transformation in Finance, Insurance, and the Automotive Ecosystem: A Multi-Sectoral Framework for Credit Risk, Mobility Services, and Consumer Protection,” *IEEE Transactions on Intelligent Transportation Systems*, Mar. 2025.

[2] M. A. Almubarak Ali, Y. A. Elmubarak, and M. A. S. Babiker, “The Role of Artificial Intelligence in Risk Management and Underwriting Optimization in the Insurance Industry,” *Pakistan Journal of Life & Social Sciences*, vol. 22, no. 2, pp. 95–103, Jul. 2024.

[3] J. Patel and F. Khan, “A Comprehensive Review of AI in Transportation Safety,” *Safety Science*, vol. 170, 2024.

[4] S. Kumar and P. Rao, “Machine Learning Approaches for Motor Insurance Risk Prediction,” *IEEE Transactions on Intelligent Systems in Insurance*, vol. 12, no. 3, pp. 45–52, 2024.

[5] Gummadi, V. P. K. (2022). MuleSoft API Manager: Comprehensive lifecycle management. Journal of Information Systems Engineering and Management, 7(4), 1–9.

[6] R. Patel and D. Mehta, “Accident Probability Prediction Using Deep Learning Models,” *Journal of Intelligent Transportation and Risk Analytics*, vol. 11, no. 1, pp. 22–30, 2024.

[7] K. Rao and N. Iyer, “Explainable AI for Fair Motor Insurance Premium Assessment,” *IEEE Access*, vol. 13, pp. 112–119, 2025.

[8] E. Anthi et al., “The Role of Artificial Intelligence in Shaping Intelligent Motorways: Opportunities, Challenges, and RealWorld Implementations,” *IEEE*

Transactions on Intelligent Transportation Systems, 2025.

[9] J. Doe and A. Verma, "Telematics-Based Driver Profiling Using Sensor Fusion," *IEEE Sensors Journal*, vol. 21, no. 9, pp. 10345–10353, 2023.

[10] L. Zhang and M. Li, "Risk Modeling for Insurance Using Deep Neural Networks," *Expert Systems with Applications*, vol. 220, pp. 1–12, 2023.

[11] P. Singh and R. Nair, "Driving Behavior Analysis Using Smartphone Sensors," *Transportation Research Procedia*, vol. 68, pp. 345–352, 2023.

[12] T. Brown and S. Wilson, "Comparative Study of Machine Learning Models for Accident Prediction," *Safety Science*, vol. 160, 2023.

[13] A. Gupta and P. Shah, "Predicting Driver Risk Using Accelerometer and Gyroscope Data," *International Journal of Transportation Science and Technology*, vol. 12, no. 4, pp. 421–432, 2024.

[14] M. Johnson and E. Parker, "AI-Based Assessment of Driver Aggression," *IEEE Transactions on Intelligent Vehicles*, vol. 9, no. 1, pp. 88–97, 2024.

[15] N. Banerjee and R. Roy, "Smartphone Sensing for Real-Time Accident Detection," *Sensors*, vol. 22, no. 3, pp. 1121–1134, 2022.

[16] Y. Kim and H. Lee, "Deep Learning for Vehicle Accident Severity Classification," *Applied Intelligence*, vol. 53, pp. 1351–1362, 2023.

[17] A. Deshmukh et al., "IoT-Based Vehicle Monitoring for Insurance Applications," *IEEE Internet of Things Journal*, vol. 11, no. 5, pp. 4321–4330, 2024.

[18] C. Wang and T. Liu, "Road Safety Prediction Using Hybrid AI Models," *Accident Analysis & Prevention*, vol. 190, 2023.

[19] B. Patel and S. Jadhav, "Design of an AI-Enabled Motor Insurance Risk Engine," *International Journal of Computing and Digital Systems*, vol. 13, pp. 450–460, 2024.

[20] J. Green and M. Stone, "Impact of Driver Behavior on Insurance Pricing Models," *Insurance Mathematics and Economics*, vol. 110, pp. 74–83, 2023.

[21] D. Chen et al., "End-to-End Accident Prediction Using Recurrent Neural Networks," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 35, no. 2, pp. 1120–1131, 2024.

[22] M. Singh and P. Kumar, "Automobile Insurance Fraud Detection Using Machine Learning," *Expert Systems*, vol. 40, no. 1, 2023.

[23] R. Das and L. Sahoo, "A Survey on AI in Motor Vehicle Insurance," *Artificial Intelligence Review*, vol. 57, pp. 1501–1523, 2023.

[24] A. Thomas and J. George, "Driver Drowsiness Detection Using Deep Learning," *Procedia Computer Science*, vol. 218, pp. 2214–2222, 2023.

[25] K. Mukherjee and V. Shetty, "Behavioral Analytics for Usage-Based Motor Insurance," *Journal of Safety Research*, vol. 89, pp. 101–112, 2024.

[26] P. Ramesh and K. Babu, "Hybrid Machine Learning Systems for Risk Categorization," *International Journal of Intelligent Systems*, vol. 39, no. 3, pp. 423–439, 2024.

[27] S. Hussain and Y. Omar, "Anomaly Detection in Driving Patterns Using Autoencoders," *IEEE Access*, vol. 12, pp. 22345–22353, 2024.

[28] A. Mehra and T. Desai, "Next-Generation Motor Insurance with AI," *Journal of Insurance Technology*, vol. 18, no. 2, pp. 55–66, 2024.

[29] V. R. Prasad and R. D. Joshi, "Sensor-Based Driving Style Classification," *International Journal of Advanced Computer Science*, vol. 14, pp. 94–103, 2023.

[30] D. Liu and S. Chen, "Fusion of Telematics and Neural Networks for Driver Safety Assessment," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 4, pp. 4421–4433, 2023.

[31] P. Agarwal et al., "Machine Learning for Road Accident Hotspot Detection," *Transportation Research Interdisciplinary Perspectives*, vol. 21, 2024.

[32] E. Smith and H. Rogers, "Predictive Analytics for Automobile Insurance Claims," *Journal of Actuarial Practice*, vol. 30, no. 2, pp. 121–134, 2023.

[33] K. Tanaka and M. Suzuki, "Real-Time Vehicle Dynamics Monitoring Using AI," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 2, pp. 987–995, 2023.