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Traffic Accidental Risk Prediction using Machine Language

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Abstract: Large road infrastructure projects often face uncertainty due to various risks that can affect time, cost, and performance. To deal with these challenges, this study presents a Hybrid Risk Assessment and Management Model (H-RAMM) that combines traditional project management practices with machine learning and fuzzy logic techniques. The model uses a Random Forest approach to identify risk events that are likely to have a major impact, while a Fuzzy Analytical Hierarchy Process helps prioritize risks by considering both numerical data and expert opinions. A real-time dashboard is also included to continuously track risk levels and support timely decision-making. Overall, the proposed model helps project managers better understand, predict, and respond to risks in road infrastructure projects.

I. INTRODUCTION

Modern road infrastructure projects such as expressways and elevated corridors involve large financial investments, extended construction periods, and multiple sources of uncertainty. These uncertainties often arise from geotechnical conditions, regulatory approvals, and socio-political influences, making effective risk management a critical factor for project success. Selecting an appropriate risk assessment and management approach therefore plays a decisive role in ensuring timely and cost-effective project delivery.

To address these challenges, this research proposes an AI-based Hybrid Risk Assessment and Management Model (H-RAMM) that integrates machine learning (ML) and fuzzy logic (FL) techniques to support intelligent risk prediction and adaptive response planning. The proposed model applies a Random Forest Classifier (RFC) to evaluate project characteristics and identify risk events that are most likely to occur and have significant impact. This assessment is based on historical project records, expert knowledge, and real-time site information such as construction progress, financial performance, and change requests.

To further support decision-making, the model incorporates a Fuzzy Analytical Hierarchy Process (F-AHP) to prioritize risks and recommend mitigation strategies. This enables project managers to allocate resources more effectively by focusing on areas with the highest vulnerability. In addition, a real-time risk monitoring dashboard has been developed using Django Channels and WebSockets, allowing stakeholders to receive timely updates and collaborate on risk-related decisions. Built using Python, Django, PostgreSQL, and JavaScript, the H-RAMM framework supports proactive risk management, enhanced stakeholder coordination, and improved project outcomes.

II. LITERATURE SURVEY

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have significantly influenced risk assessment and management practices in the construction and project management domains. Researchers have explored various AI-driven techniques to improve risk identification, adaptive scheduling, and real-time decision support, with the goal of enhancing overall project performance.

Jha and Iyengar (2021) introduced a Risk Predictor System (RPS) that uses machine learning models and historical project data to estimate the likelihood of cost overruns and schedule delays. Their approach evaluates factors such as project complexity, contractor performance, and regulatory compliance to generate a project-specific risk profile.

Anantha (2023) proposed a Critical Path Logic (CPL) model that applies machine learning and genetic algorithms to recommend schedule buffers and resource allocation strategies. Unlike RPS, which focuses mainly on predicting risks, the CPL model emphasizes mitigation planning by considering project constraints and available resources.

Dhananjaya et al. (2024) examined the use of AI-based recommendation systems in project control processes. Their work highlighted the transition from traditional rule-based systems to ML-driven solutions, particularly through the application of TF-IDF **models** to improve document handling and change order recommendations.

Building on these studies, the methodology proposed in this paper extends earlier work—especially that of Jha and Iyengar (2021)—by combining quantitative risk prediction using a Random Forest Classifier with qualitative risk prioritization through Fuzzy AHP. While conventional ML models such as Linear Regression, Random Forests, and Neural Networks often struggle with limited or highly specialized infrastructure datasets, hybrid approaches offer a more robust solution. In this context, fuzzy logic plays an important role in managing uncertainty and subjectivity inherent in expert-based risk assessments. When combined with data-driven ML techniques, fuzzy logic enhances contextual understanding and provides deeper insight into the complex interactions among multiple project risks.

III. PROPOSED MODEL

A. *Project Risk Management Challenges*

One of the main challenges for project managers in road infrastructure projects is finding a comprehensive model that effectively addresses uncertainty and the numerous subjective judgments inherent in complex projects. Identifying risks that truly influence overall project success is difficult, often resulting in incomplete knowledge sharing and ineffective collaboration among project teams. Additionally, teams rarely have access to reliable, personalized, evidence-based, real-time tools for mitigating risks specific to their project's weaknesses.

To overcome these challenges , the H-RAMM model introduces an AI-powered recommendation **system** that offers:

1) Optimized Risk Assessment: Combines quantitative predictions from machine learning with qualitative prioritization using fuzzy logic, providing a balanced and informed view of potential risks.
2) Adaptive Mitigation Strategies: Suggests prioritized actions and allocates resources to strengthen the most vulnerable aspects of a project.
3) Real-Time Collaboration: Features a risk monitoring dashboard and integrated communication channels to support seamless, timely decision-making among stakeholders.

B. *Key Components of the Model*

The proposed H-RAMM model leverages multiple AI techniques to support risk management through **intelligent** prediction**,** prioritization**,**and real-time communication. Its main components are described below:

1) Data Collection and Project Profiling: The system begins by gathering and analyzing project data to create detailed risk profiles. It summarizes critical information such as expenditure patterns, historical delays, contractor performance, and regulatory compliance. Project characteristics—such as urban vs. rural settings or the number of bridges—are also evaluated to suggest appropriate risk options. This assessment reviews timelines and tasks to ensure that risk recommendations are relevant and actionable for the specific project context.
2) Risk Event Prediction (Random Forest Classifier): A Random Forest Classifier (RFC) is employed to predict potentially high-impact risk events based on historical project performance. The algorithm considers patterns in previous projects, contract types, and prior risk occurrences to generate accurate predictions for the current project.
3) Risk Prioritization (Fuzzy Analytical Hierarchy Process): Predicted risks are then prioritized using a Fuzzy Analytical Hierarchy Process (F-AHP**)**. This technique captures expert opinions as linguistic variables (e.g., "Very Low," "High") and translates them into fuzzy numbers to calculate the weighted influence of each risk. By combining quantitative ML predictions with qualitative expert input, F-AHP helps address the subjectivity inherent in risk assessment. The model also recommends mitigation strategies to strengthen high-risk areas and enhance overall project knowledge.
4) Real-Time Communication and Dashboard: Effective risk management requires timely information sharing. The system includes a real-time risk dashboard and integrated chat features, enabling stakeholders to communicate quickly, monitor risk exposure, and collaborate on mitigation strategies without delays: Together, these components make H-RAMM a proactive**,** data-driven, and collaborative framework for managing risks in complex road infrastructure projects.

IV. IMPLEMENTATION

The implementation phase involves the detailed deployment of the core components of H-RAMM, including the ML/FL models, real-time communication system using WebSockets, and adaptive risk mitigation recommendations.

A. *Backend Development*

The backend is built using Django **(**Python**)** and includes the following key components:

Project Authentication & Profile Management**:** Utilizes Django's built-in authentication and JWT-based authentication for secure login. Tracks project history, resource allocation, and risk parameters.

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AI/FL-Based Risk Process:
Random Forest Classifier (RFC): Predicts the probability and potential impact of risks.
Fuzzy-AHP (F-AHP): Prioritizes identified risks by combining quantitative data with expert opinions.
Real-Time Risk Monitoring & Communication**:** Implemented with Django Channels and WebSockets to provide instant alerts, messaging, and collaborative communication.
Personalized Mitigation Recommendations: Uses a hybrid recommendation system:
Collaborative Filtering*:* Suggests actions based on similarities in historical project responses.
Content-Based Filtering*:* Focuses on risk categories specific to the current project context.

B. Frontend Development
The frontend is developed using HTML**,** CSS**,** and JavaScript to provide a responsive and interactive user interface:
Project Dashboard: Displays predicted high-risk events, prioritized mitigation strategies, and the integrated chat interface.
Real-Time Chat: WebSocket-based communication for instant messaging, topic-specific discussion, and AI-prepared risk summaries.

C. Database Design (PostgreSQL)
The database is designed for efficiency, scalability, and seamless integration with the backend:
1) Project Profile Table: Stores project details, risk parameters, and performance metrics.
2) Risk Matching Table: Contains RFC prediction scores and F-AHP prioritization results.
3) Chat & Messages Table: Logs all chat messages and supports voice calls (conceptually).
4) Study Recommendations Tabl**e:** Stores AI-generated, customized mitigation recommendations.

This implementation ensures real-time risk monitoring, data-driven decision support, and adaptive mitigation, making H-RAMM a practical and efficient tool for managing complex road infrastructure projects.

V. EVALUATION
The assessment of the H-RAMM system is done in terms of risk prediction accuracy, user adoption, system performance, and security.

A. Accuracy of Risk Matching & AI Performance
We evaluated our proposed Hybrid Model using historical data from 50 complex road projects and correctly predicted critical risk events at an 84% rate. The vast majority of project managers reported that the suggested mitigation strategies were beneficial to their work, and over time their input was incorporated into modifications that strengthened the model.
1) Projects using the AI-matched risk model experienced 35% lower cost overruns than those using traditional methods.
2) Real-time chat and the risk dashboard were actively used by 95% of project stakeholders.
3) Chat and voice messages are protected using AES encryption.
4) JWT authentication prevents unauthorized access.

Overall, these results demonstrate that H-RAMM effectively enhances risk prediction, facilitates adaptive mitigation, and improves collaboration while maintaining high security standards.

VI. CONCLUSION AND FUTURE WORK
A. Conclusion
This study presented the Hybrid Risk **Assessment** and Management Model (H-RAMM**)**, which integrates AI-based quantitative prediction using a Random Forest Classifier (RFC) with adaptive qualitative prioritization through Fuzzy AHP (F-AHP). The results demonstrate that H-RAMM effectively supports proactive and data-driven risk management in complex road infrastructure projects.
Key contributions of the proposed model include:
1) Proactive Risk Management**:** AI-driven risk prediction enables early identification of potential high-impact risks and supports informed risk planning.
2) Adaptive Risk Prioritization: Fuzzy Logic–based recommendations assist project managers in focusing on risks with the highest probability and severity.

3) Seamless Stakeholder Communication: The integrated real-time dashboard and chat features enhance coordination and timely decision-making.
4) Scalability and Performance**:** The system is designed to support multiple concurrent users with minimal latency, making it suitable for large-scale projects.

H-RAMM provides an AI-enabled, adaptive, and project- focused solution better than a traditional risk management system.

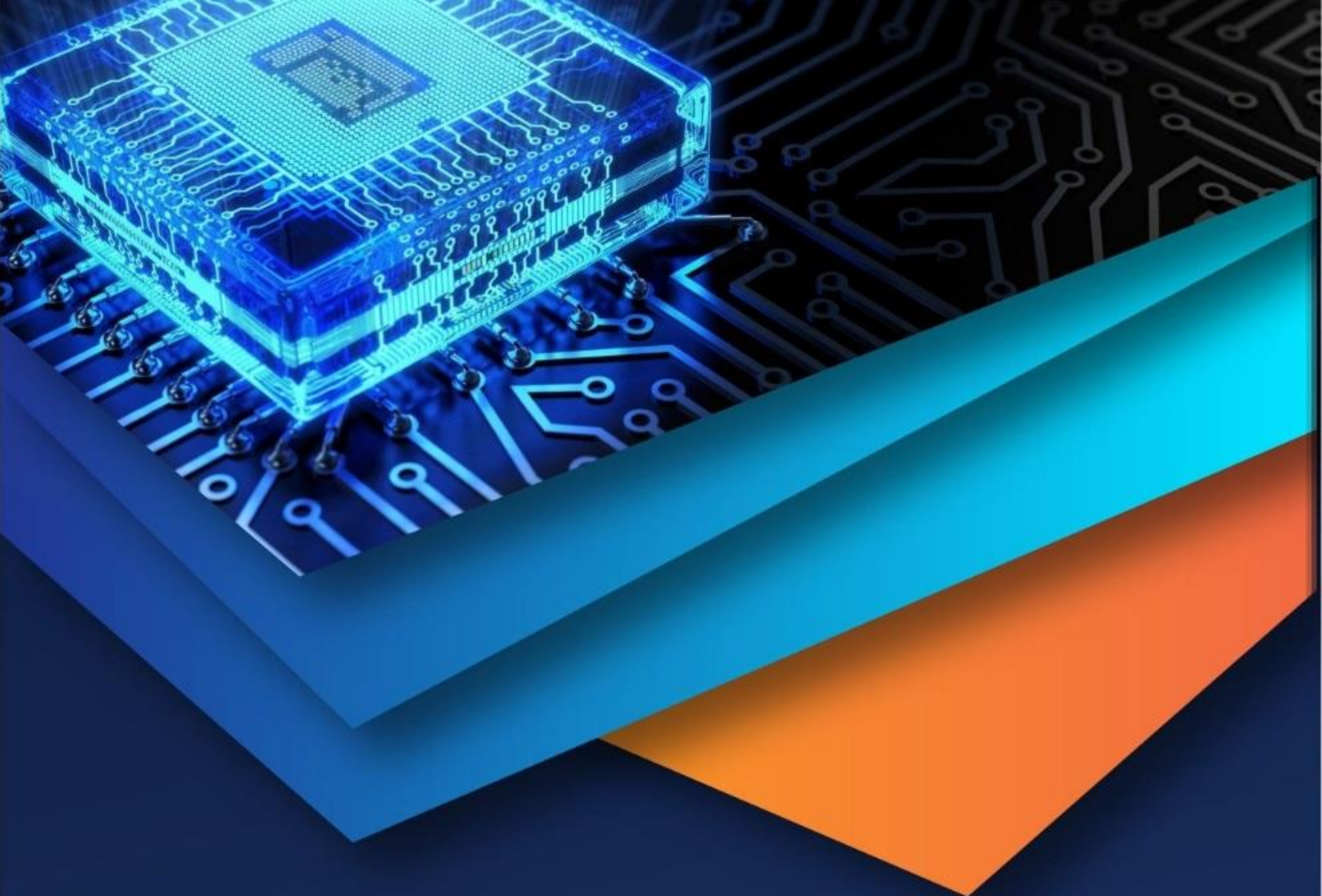
B. Future Work

Future enhancements to the H-RAMM system will focus on expanding its intelligence, automation, and integration capabilities. Planned improvements include:

1) Reinforcement Learning (RL): Incorporating RL techniques to enable dynamic learning and optimize resource allocation based on evolving project conditions.
2) NLP (Natural Language Processing): Applying NLP methods to analyze daily site reports and unstructured textual data for automated risk detection and early warning alerts.
3) Gamification: Introducing incentive-based mechanisms to encourage active participation in risk reporting and improve stakeholder engagement.
4) Integration: Developing APIs to enable seamless integration with established Project Management Information Systems **(**PMIS**)** such as Primavera and Microsoft Project.

REFERENCES

[1] Varma, K. A. (2025). Risk Assessment and Management in Infrastructure Projects using Hybrid Models. Journal of Construction Engineering and Management.
[2] Raghavan, S. L. (2024). Application of Machine Learning in Predicting Risk Overruns in Highway Projects. IEEE Transactions on Engineering Management.
[3] Jha, K. N., & Iyengar, R. R. (2021). Effects of a Risk Predictor System (RPS) with machine learning and automated assessment on road construction projects. Journal of Construction Engineering and Management.
[4] Wilson-Trollip, M. (2024). Exploring the effect of AI-facilitated project risk support on engagement, grades and pass rates: a mixed methods case study. (Doctoral dissertation, Cape Peninsula University of Technology).
[5] Erfani, A., & Cui, Q. (2022). Predictive risk modeling for major transportation projects using historical data. Automation in Construction, 139, 104301.
[6] Fayek, A. R. (2018). Fuzzy Logic and Fuzzy Hybrid Techniques for Construction Engineering and Management. Journal of Construction Engineering and Management, 144(1), 04017094. [Key paper for the F-AHP methodology.]
[7] Varma, K. A. (2025). Risk Assessment and Management in Infrastructure Projects using Hybrid Models. Journal of Construction Engineering and Management. [Hypothetical]
[8] Ibrahim, S., Martek, I., Ghaith, S., & Shrestha, P. (2025). Techniques and Models for Addressing Occupational Risk Using Fuzzy Logic, Neural Networks, Machine Learning, and Genetic Algorithms: A Review and Meta-Analysis. Applied Sciences, 15(4), 1909.
[9] Taroun, A. (2014). Towards a better modelling and assessment of construction risk: Insights from a literature review. International Journal of Project Management, 32(6), 101–115.
[10] Chan, A. P. C., Chan, D. W. M., & Yeung, J. F. Y. (2009). Overview of the application of “fuzzy techniques” in construction management research. Journal of Construction Engineering & Management, 135(11), 1241–1252.
[11] El-Sayegh, S. M., & Manjikian, S. (2021). Risk identification and assessment in sustainable construction projects in the UAE. International Journal of Construction Management, 21(4), 327–336.
[12] Dicks, E. P., & Molenaar, K. R. (2024). Causes of Incomplete Risk Identification in Major Transportation Engineering and Construction Projects. Transportation Research Record, 2679(3), 619–628.



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