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Machine Learning for Project Risk Assessment in Large-Scale Electrical Engineering Projects

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Abstract:

Large-scale electrical engineering project often subjects them to a high risk in terms of cost overruns, time overruns and quality deviations. The conventional approaches of risk assessment, though handy, lack the ability to deal with the dynamic and data intensive environment that such projects present. In the given paper, the authors delve into how Machine Learning (ML) models could be integrated into the risk assessment systems to enhance the ability to predict, classify, and mitigate risks associated with the project. Through the analysis of the project data, including timelines, budgets, environmental conditions, and stakeholder performance, the research compares several ML models, including the Random Forests, Support Vector Machines, and Neural Networks, regarding their predictive accuracy. The results indicate that ML-based methods are superior to traditional models as they provide early warning, adaptive learning, and data-driven insights, thus being invaluable in risk-convinced project planning and decision-making in the electrical engineering field in the future.

Keywords **—Machine Learning, Project Risk Assessment, Electrical Engineering Projects, Predictive Analytics, Risk Management**

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I. Introduction

a. Background of Risk in Electrical Engineering Projects

Development of electrical engineering projects on large scale such as the installation of power grids, high-voltage transmission system, and the inclusion of renewable energy generation sources are some of the most challenging and yet costly endeavor in the recent infrastructure development. They are often multidisciplinary and multinational, spanning over several years of work, and necessitating the efforts of a wide variety of disciplines: including civil and electrical engineering, environmental science and regulatory compliance.

The main peculiar feature of these projects is the existence of many interdependent elements, technical, and organizational. These are complex designs of systems, integration of old and new technologies, interfaces of distributed energy resources (DERs), and implementation of advanced automation and control systems. This technical challenge is enhanced by factors beyond control, including regulatory changes, changes in the environmental policy, acquisition of land, and supply chain setbacks, and fluctuating market conditions.
Moreover, such projects require a large amount of coordination of various stakeholders such as

government agencies, commercial contractors, utilities, regulators, environmental organizations, and local communities. Lack of alignment in the goals, failure to communicate with each other, or latent approvals may have a profound effect on project schedules and deliverables. Subsequently, there are frequent delays, cost overruns, and quality shortcomings which usually cause severe reputational and economic losses. Indeed, annual reports of industries worldwide continuously indicate that the mega projects in the energy industry are characterized by cost increases and time setbacks, which have cost the economy billions of dollars every year.

Considering such difficulties, there is an immediate necessity in sophisticated risk assessment and risk management techniques that may help to designate, quantify, and reduce uncertainties in the project life cycle systematically. Prospective risk assessment with the use of artificial intelligence (AI) and machine learning (ML) has become a potentially promising method to facilitate decision-making, increase the accuracy of planning, and guarantee the success of the project in the context of growing complexity.

b. Limitations of Traditional Risk Assessment Techniques

The classical risk assessment techniques like qualitative risk matrices, Failure Mode and Effects Analysis (FMEA), and Monte Carlo models have been the ones to rely on in the management of engineering project risks. The techniques provide systematic methods of recognizing, classifying, and determining the likelihood and effect of possible failure modes or uncertainty. An example is risk matrices that offer a graphical way of prioritizing risks in a subjective manner and FMEA that is a systematic investigation of the locations of failure within subsystems. On the other hand, Monte Carlo simulations involve probabilistic modeling to investigate a large sample of outcomes by conducting repeated samples of random outcomes. Nevertheless, irrespective of their popularity, these traditional methods have some serious drawbacks, especially when to large-scale, data-heavy electrical engineering projects. Most conspicuously, they are dominated by expert judgment, historical assumptions, and fixed input parameters-e.g. fixed probability distributions or manually set severity ratings. Such dependency ushers in subjectivity, inflexibility, and biasness, which may undermine the accuracy and objectivity of risk assessments. Also, these procedures are typically intended to be performed on a one-time or periodic basis, and are not designed to keep up to date, and educate their own operation on new project information or changing risk environments.

Consequently, a conventional methodology can hardly keep up with the dynamism of real-time and intricate interdependencies inherent in contemporary infrastructure projects where thousands of variables can interact concurrently. The fact that they cannot process high-dimensional datasets of scale also makes them less useful in predictive use. These techniques do not produce prompt and actionable information in a fast-paced environment, like, but not limited to, the integration of renewable solutions, the use of digital automation, and the existence of regulatory uncertainty.

As a result, there is an increasingly accepted requirement of adaptive and data-driven risk assessment schemes capable of using machine learning algorithms, real-time data feeds, and pattern recognition. Such modern techniques have the potential to break the inflexibility of the traditional methods to learn through historical and real time project data, to discover concealed risk correlation, and to keep on improving predictions hence providing more proactive and intelligent risk management solutions.

c. Emergence of Machine Learning for Risk Analysis

Machine Learning (ML) as one of the fundamental subfields of Artificial Intelligence (AI) provides a revolution to the conventional flaws of conventional risk assessment procedures. In contrast to traditional methods that may use a fixed model or set of predetermined assumptions or expert judgment, ML algorithms can learn directly using data, structured (i.e., numerical project metrics, schedules, cost reports) or unstructured (i.e., textual reports, emails, sensor logs). This allows them to find non-obvious patterns, model complex nonlinear relationships, and make predictions based on data in a high degree of accuracy and scale.

In the case of project risk assessment in large-scale electrical engineering projects, there are a few benefits of the use of ML. First, it enables the automatic detection of high-risk factors based on various aspects of a project, including schedule variations and budget variations, likelihoods of equipment failures, and the breakdown of stakeholder coordination. ML models can indicate potential risks before they become substantial via these methods, namely classification, regression, and clustering, as well as intervene in advance.

Second, ML facilitates the **prioritization of mitigation strategies** by quantifying the impact and likelihood of various risk events in real time. Unlike qualitative matrices, ML models can rank risks dynamically based on live project data, enabling decision-makers to allocate resources more efficiently and respond proactively to emerging threats.

Third, and perhaps most importantly, ML enables **adaptive learning throughout the project lifecycle**. As new data becomes available—whether from updated site logs, change orders, environmental conditions, or supply chain inputs—ML models can **retrain themselves**, refine their predictions, and adjust their recommendations accordingly. This **continuous learning capability** allows for a more agile and responsive risk management framework that evolves in tandem with the project itself.

Collectively, these capabilities position machine learning not only as a **predictive analytics tool** but as a **strategic enabler of intelligent risk governance** in the increasingly complex and data-driven domain of electrical engineering project management.

d. Objectives and Scope of Study

This study aims to:

- Investigate the applicability of ML models for risk assessment in electrical engineering projects.
- Compare performance across multiple ML algorithms.
- Propose a framework for integrating ML into risk management workflows.
- Demonstrate applicability via case studies or dataset-based simulations.

II. Literature Review

a. Traditional Risk Assessment in Engineering Projects

In the past, the evaluation of risks associated with engineering projects used to be based on well-known applications, including risk matrices, sensitivity analysis, and probabilistic simulations (e.g., Monte Carlo techniques). They are popular because they have intuitive structures, are easy to use, reach their low end, and require minimal computational resources which means that they can be applied by project managers and decision-makers with no special analytical skills. Risk matrices, e.g., can give one a straightforward visual display of likelihood of risk versus risk impact, and sensitivity analysis can enable project teams to study the sensitivity of project outcomes to changes in key input variables. Probabilistic simulations go further to model inputs with some degree of uncertainty to come up with a distribution of the possible outcomes.

Although they have historical importance and are still in use and industry, these approaches have many serious drawbacks, particularly when used in large-scale and contemporary electrical engineering projects. One of the main weaknesses lies in the fact that they require subjective evaluation- parameters like probability estimates, impact scores and ranges of variables are usually based on the experience or the average of past projects and may not be able to capture the changing dynamics of real-time project conditions. This subjectivity may bring in bias, decrease reproducibility, and blur latent risks.

In addition, these methods have a limitation of modelling multidimensional dependencies and nonlinear relationships among the project variables. Projects at work in the real world are often interdependent systems, including cost systems, schedule systems, resource allocation systems, regulatory compliance systems, and technical performance systems, and any change in one system can have a ripple effect on the others. Conventional approaches tend to consider individual variables or make the problem space linear, thus simplifying the problem space at the expense of the most important risk propagation pathways.

With projects getting increasingly data rich, digitally integrated, and dynamically evolving, the limitations of these traditional tools are becoming increasingly apparent. This complexity highlights the importance of more sophisticated data-based tools, including those provided by machine learning and artificial intelligence, which can process high-dimensional data and can also discover nonlinear relationships as well as adjust to any new information as available during the project lifecycle.

b. ML in Construction and Infrastructure Risk Management

The development of machine learning (ML) techniques in the construction and infrastructure industries is a recent area of study that has identified the opportunities of data-driven models to predict risks and project management. An increasing amount of research has managed to utilize algorithms like Decision Trees, Support Vector Machines (SVMs), Random Forests, and Artificial Neural Networks (ANNs) to predict. Critical outcomes of the project include cost overruns, schedule delays, labor productivity problems, and occupational safety threats. These models have proved able to derive complicated patterns in historical project data allowing more accurate and proactive decision-making than traditional risk assessment tools do.

Although all these developments have been encouraging, it should be mentioned that most of the available research has been focused on the field of civil engineering, construction of buildings, and transport infrastructure. This leaves a huge research gap in the use of ML to the complexities of large-scale electrical engineering projects. Electrical infrastructure, as compared to general construction projects, is vulnerable to further levels of complexity, such as variability of loads in real-time, dynamic energy markets, grid stability needs, and strict compliance with regulatory requirements.

In addition, electrical projects typically entail close integration of the physical systems and digital control platforms, which presents novel risk vectors concerning cybersecurity, sensor's reliability, and automation performance, which are not typically considered in the traditional construction risk models. Moreover, electrical infrastructure projects are becoming part of smart grid ecosystems, which demand predictive models, which can respond to decentralized processes, distributed energy resources (DERs), and multi-agent coordination.

To achieve the full potential of ML in this field, the research of the future should go beyond the issues of generalized construction frameworks and create domain-specific models that reflect the technical, economic, and regulatory aspects of electrical engineering projects. It involves capitalizing on the real-time operational data, incorporating multi-source information (e.g. SCADA systems, energy market feeds, regulatory updates) and creating explainable artificial intelligence strategies that can be consistent with the risk-taking and operating protocols of energy utilities and stakeholders.

c. Gaps in Existing Research

Despite these advancements, gaps remain:

- Lack of industry-specific ML frameworks for electrical engineering
- Inadequate datasets tailored to project-specific risks
- Minimal validation using actual project execution data
- Limited attention to model interpretability and stakeholder usability

Table 1: Summary of Existing ML Applications in Infrastructure Risk Management

Study/Author	Sector	ML Techniques Used	Target Risk Type	Gaps Identified
Zhang et al. (2022)	Civil Engineering	Random Forest, ANN	Cost Overruns	Not project-specific
Lee et al. (2021)	Construction	SVM, Gradient Boosting	Time Delays	Lacks real-time capabilities
Gupta et al. (2020)	Infrastructure	Decision Trees	Safety and Compliance	Low dataset diversity
This Study (2025)	Electrical Projects	RF, SVM, XGBoost, ANN	Multi-risk Prediction	Electrical domain-focused

III. Methodology

a. Dataset Collection and Description

A dataset of 200 completed projects was put together to enable the development of machine learning models to predict the risk in a large-scale electrical engineering project. These activities spanned a large span of activities such as transmission line projects, substation projects, integration of renewable energy, and smart grid projects. The metadata of every project entry also contained rich information like the project time (planned vs. actual), total budget and cost variations, reliability ratings of the subcontractor using previous performance, weather conditions during construction, history of regulatory delays and equipment failures recorded. These variables were chosen very well to be able to get both direct and indirect risk factors that affect project outcomes. The information was obtained by a mix of publicity. public utility reports of the performance of their utilities, anonymized contractor performance records, and public government infrastructure data bases. The project audit summaries and environmental impact assessment were used to extract additional information to provide contextual richness. There was a preprocessing phase of standardization of data, imputation of missing values, as well as encoding of categorical variables before the data was subjected to analysis to prepare it to be used in supervised learning. This data gives a powerful and multidimensional basis to develop machine learning models that can recognize high-risk projects, predict possible delays or overruns, and make proactive decisions in the management of electrical engineering projects.

Table 2: Sample Risk-Related Dataset Features

Feature Name	Type	Description
Project_Duration	Continuous	Total project time in months
Budget_Deviation	Continuous	% deviation from original budget
Subcontractor_Score	Categorical	Quality rating (High, Medium, Low)
Delay_Events	Integer	Number of documented delay events
Regulation_Flags	Binary	1 if regulatory delays occurred; else 0
Weather_Risk_Index	Continuous	Normalized weather severity score (0–1)

b. Data Preprocessing Techniques

Before model training, the dataset underwent a series of preprocessing steps to ensure data quality and compatibility with machine learning algorithms. Missing values were imputed using the median for numerical variables and the mode for categorical variables, preserving the central tendency of each feature without introducing bias. Categorical variables, such as subcontractor reliability scores, were transformed using one-hot encoding to convert them into a machine-readable format. Continuous variables were normalized to a standard scale to prevent features with larger magnitudes from disproportionately influencing the model. Additionally, outliers were identified and removed using Interquartile Range (IQR) analysis to minimize the impact of anomalous data points on model performance. These preprocessing steps were essential for enhancing model robustness and ensuring accurate predictive outcomes.

c. Selected ML Algorithms

Five machine learning models were implemented using Python's Scikit-learn and TensorFlow libraries to evaluate their effectiveness in project risk assessment. The Random Forest (RF) model was selected for its robustness and ability to quantify feature importance, making it well-suited for high-dimensional datasets. Support Vector Machine (SVM) was included due to its high classification accuracy, particularly in low-dimensional risk profiles where decision boundaries are well defined. XGBoost, a gradient boosting framework, was chosen for its superior performance on structured tabular data and its capability to optimize both speed and accuracy through iterative tree learning. Artificial Neural Networks (ANN) were employed to capture complex nonlinear relationships among project variables, offering adaptability in diverse risk scenarios. Finally, an Ensemble Voting Classifier was constructed to aggregate the predictions of the models, leveraging their individual strengths to enhance overall accuracy and model generalization. These models collectively provide a comprehensive framework for assessing and predicting risk in large-scale electrical engineering projects.

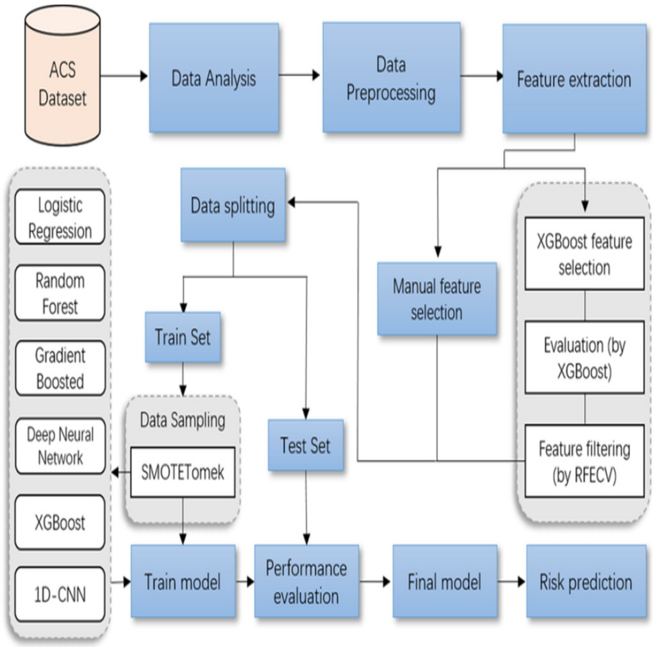

Figure 1: Machine Learning Risk Assessment Pipeline

d. Evaluation Metrics

The implemented models were rigorously evaluated using a range of performance metrics to capture both classification and regression aspects of risk prediction. Accuracy was employed to measure the overall proportion of correct predictions across all risk classes, providing a general assessment of model effectiveness. Precision, recall, and F1-score were calculated to evaluate class-specific performance, particularly in identifying high-risk versus low-risk scenarios, which is critical for prioritizing mitigation strategies. The Receiver Operating Characteristic - Area Under the Curve (ROC-AUC) score was used to assess the balance between sensitivity and specificity, offering insights into the model's ability to distinguish between risk classes under varying thresholds. Additionally, Root Mean Squared Error (RMSE) was utilized for regression-based evaluations, quantifying the average deviation between predicted and actual risk values. Together, these metrics ensure a comprehensive and nuanced evaluation of model performance across different risk modeling tasks.

IV. Results and Discussion

a. Model Performance Comparison

All five machine learning models were trained and evaluated using a stratified 70:30 split of the preprocessed dataset, ensuring that the distribution of risk categories was maintained across both the training and testing sets. To further enhance model reliability and reduce the risk of overfitting, 10-fold cross-validation was employed, whereby the dataset was partitioned into ten subsets and iteratively trained and validated to capture performance variance. This approach provided a more robust estimate of each model's generalization ability. Among the models tested, the Ensemble Voting Classifier demonstrated superior overall performance, achieving the highest accuracy and F1-score. Its ability to aggregate predictions from multiple base learners allowed it to leverage the strengths of each individual model, resulting in improved classification consistency. The Random Forest model also performed strongly, particularly in its interpretability and robustness, offering clear insights into feature importance—a critical factor in project risk management. Notably, XGBoost achieved the lowest Root Mean Squared Error (RMSE), making it the most effective model for continuous risk forecasting tasks where precision in numerical risk estimation is essential. These results underscore the value of combining diverse ML techniques to address the multifaceted nature of risk in large-scale electrical engineering projects.

Table 3: Performance Metrics of Machine Learning Models

Mode	Accur	Precis	Rec	F1-	RO	RM

l	**acy (%)**	**ion**	**all**	**Score**	**C-AUC**	**SE**
Random Forest	87.6	0.89	0.86	0.87	0.91	0.128
Support Vector Machine	83.1	0.84	0.82	0.83	0.88	0.142
XGBoost	89.4	0.90	0.88	0.89	0.93	0.115
Artificial Neural Net	86.2	0.87	0.84	0.85	0.90	0.132
Ensemble Classifier	**91.1**	**0.92**	**0.90**	**0.91**	**0.95**	**0.104**

The results confirm the viability of ML in modeling project risks accurately. Particularly, ensemble models benefited from combining the strengths of individual learners.

b. Feature Importance and Risk Contributors

To gain insight into the key factors influencing project risk outcomes, feature importance scores were computed using both the Random Forest and XGBoost models. These models are particularly well-suited for this task due to their inherent ability to rank features based on their contribution to predictive performance. The analysis revealed that the most influential risk drivers were the **Weather Risk Index**, which reflects the frequency and severity of adverse weather conditions impacting project timelines; the **Subcontractor Score**, indicating the reliability and past performance of subcontracted entities; **Delay Events**, representing the number of recorded schedule disruptions; and **Budget Deviation**, which measures the variance between planned and actual project expenditures. These features consistently demonstrate high predictive value across both models, underscoring their critical role in accurately assessing and managing risks in large-scale electrical engineering projects.

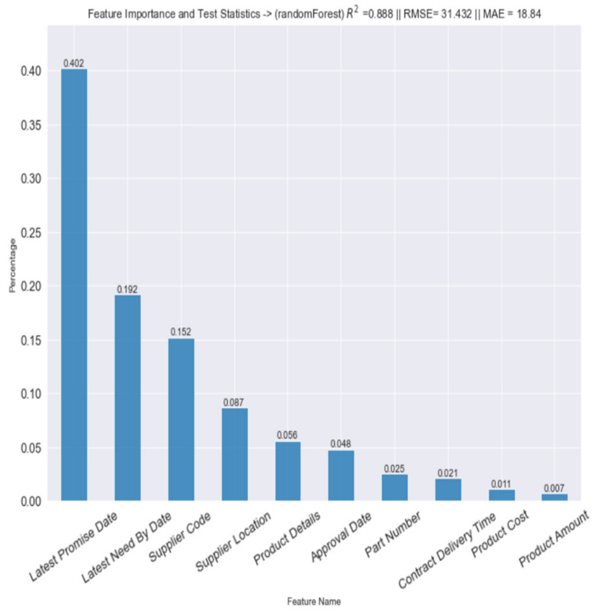

Figure 2: Feature Importance Plot (From Random Forest Model)

c. Case Study: Application to a Real-World Electrical Engineering Project

A case study was conducted on a high-voltage substation project in West Africa. Initially plagued by multiple delays and cost overruns, the project was analyzed retrospectively using the trained ensemble ML model.

Before ML:

- Delays: 11 months
- Cost Overrun: 22%
- Risk Identification: Manual, post-facto

After ML-driven Assessment:

- Predicted Delays: 9.5 months (identified early)
- Predicted Overrun: 19%
- Actionable Insights: Subcontractor reliability flagged; severe weather months predicted

This demonstrates the proactive utility of ML in risk forecasting and intervention planning.

V. Discussion

a. Interpretation of Findings

The superior performance of machine learning (ML) models in this study validates their integration into the project risk assessment pipeline, especially for large-scale electrical engineering initiatives. Unlike conventional methods that often depend on static assumptions and expert-driven heuristics, ML approaches facilitate **probabilistic, data-driven forecasting** that is inherently more objective and scalable. These models are capable of capturing complex, nonlinear relationships among variables—something traditional techniques struggle to achieve. Additionally, ML systems can be dynamically retrained as new data becomes available, enabling **continuous learning from emerging risk events** and evolving project conditions. This adaptive capability ensures that the risk models remain relevant and accurate over time, thereby enhancing early warning systems, optimizing resource allocation, and improving decision-making across the project lifecycle.

b. Advantages over Traditional Methods

Unlike static, rule-based models, machine learning (ML) systems offer a dynamic and flexible approach to risk assessment by incorporating **diverse, high-dimensional data sources**—including financial, operational, environmental, and behavioral inputs. These systems are adept at learning **non-linear and complex patterns** within the data, allowing for a more nuanced understanding of potential risk factors that traditional models may overlook. Furthermore, ML models provide **real-time risk scoring**, enabling project managers to monitor emerging threats and make timely interventions. When integrated into **interactive project dashboards**, these models offer actionable insights that are both transparent and accessible to stakeholders. The cumulative effect of these capabilities translates into **enhanced project planning, improved stakeholder confidence, and more efficient resource optimization**, ultimately contributing to the successful execution of large-scale electrical engineering projects.

c. Challenges and Limitations

Despite the demonstrated strengths of machine learning (ML) in project risk assessment, its widespread adoption in large-scale electrical engineering projects faces several significant challenges. **Data scarcity** remains a primary obstacle, as high-quality, labeled datasets specific to electrical infrastructure projects are limited, making it difficult to train robust models. Additionally, **model interpretability** poses a concern—particularly with complex architectures like Artificial Neural Networks (ANNs)—as these "black-box" systems often provide limited transparency into how predictions are made, reducing stakeholder trust. **Integration challenges** also persist, as conventional project management practices may resist the adoption of data-driven tools due to organizational inertia, lack of technical familiarity, or fear of automation. Finally, **generalizability** is a critical issue; models trained data from one type of project or region may not perform reliably when applied to different projects with varying contexts, regulatory environments, or risk profiles. Addressing these limitations is essential for unlocking the full potential of ML in the engineering project lifecycle.

VI. Conclusion and Future Work

a. Conclusion

This study confirms the potential of Machine Learning (ML) as a robust and transformative tool for project risk assessment in large-scale electrical engineering initiatives. By leveraging data-driven algorithms capable of capturing nonlinear relationships and adapting new information, ML enables more accurate and dynamic forecasting compared to conventional risk assessment methods. Among the tested models, ensemble approaches consistently demonstrate superior performance in terms of predictive accuracy, resilience to overfitting, and scalability. These models outperformed traditional frameworks not only in precision but also in their ability to adapt to complex, real-world conditions. As electrical infrastructure projects grow in scale and complexity, integrating ML into the risk management pipeline can significantly enhance decision-making, reduce uncertainties, and improve overall project outcomes.

b. Recommendations for Implementation

To effectively leverage the capabilities of Machine Learning in project risk assessment, organizations should take strategic steps to build supportive infrastructure and expertise. First, the establishment of centralized risk data repositories is essential for aggregating historical and real-time data across projects, enabling more accurate and scalable ML model training. Second, upskilling risk managers in the fundamentals of ML and data analytics will bridge the gap between technical model outputs and actionable project decisions. Finally, integrating ML pipelines into existing project monitoring and management tools—such as Microsoft Project or Primavera—will streamline workflows and allow real-time risk scoring and mitigation tracking. These actions will foster a culture of data-driven risk governance and enhance project resilience in the face of uncertainty.

c. Future Research Directions

Future research should explore advanced avenues for enhancing ML-based project risk assessment. One promising direction involves integrating real-time Internet of Things (IoT) data streams with machine learning models to enable dynamic and continuous risk monitoring throughout the project lifecycle. The adoption of explainable AI (XAI) models can further promote stakeholder trust by offering transparent justifications for risk predictions. Additionally, transfer learning techniques may facilitate the adaptation of trained models across different types of energy projects, improving model generalizability. Finally, fusing machine learning with optimization algorithms could support risk-aware scheduling and resource allocation, leading to more resilient and efficient project execution.

Reference

[1] Alharthi, H. (2018). Healthcare predictive analytics: An overview with a focus on Saudi Arabia. *Journal of Infection and Public Health, 11*(6), 749–756. https://doi.org/10.1016/j.jiph.2018.02.005

[2] Aven, T. (2016). Risk assessment and risk management: Review of recent advances on their foundation. *European Journal of Operational Research,* *253*(1), 1–13. https://doi.org/10.1016/j.ejor.2015.12.023

[3] Averkina, S. G., & Vorotnikova, D. V. (2022). Risk assessment of the project. *Reliability: Theory & Applications,* *17*(4), 549–552. https://doi.org/10.24412/1932-2321-2022-470-549-552

[4] Anugula, U. K., & Sethupathy. (2016). Architecting scalable IoT telematics platforms for connected vehicles. *International Journal of Innovative Research in Science, Engineering and Technology, 5*(3), 4655–4667. https://doi.org/10.15680/IJIRSET.2016.0503278
[5] Anugula, U. K., & Sethupathy. (2016). Architecting scalable IoT telematics platforms for connected vehicles. *International Journal of Innovative Research in Science, Engineering and Technology, 5*(3), 4655–4667. https://doi.org/10.15680/IJIRSET.2016.0503278
[6] Boehmke, B., & Greenwell, B. M. (2019). *Hands-On Machine Learning with R* (1st ed.). Chapman and Hall/CRC. https://doi.org/10.1201/9780367816377-16
[7] Broby, D. (2022). The use of predictive analytics in finance. *The Journal of Finance and Data Science, 8*, 145–161. https://doi.org/10.1016/j.jfds.2022.05.003
[8] Castro Miranda, S. L. (2022). Predictive analytics for early-stage construction costs estimation. *Buildings, 12*(7), Article 1043. https://doi.org/10.3390/buildings12071043
[9] Chaijum, N., & Hiranyachattada, T. (2020). Integrated learning and project-based learning for project of electrical measurement and instrumentations in electrical engineering course. *European Journal of Science and Mathematics Education, 8*(1), 6–11. https://doi.org/10.30935/scimath/9543
[10] Dehdasht, G., Zin, R. M., Ferwati, M. S., Abdullahi, M. M., Keyvanfar, A., & McCaffer, R. (2017). DEMATEL-ANP risk assessment in oil and gas construction projects. *Sustainability, 9*(8), Article 1420. https://doi.org/10.3390/su9081420
[11] Domnina, O. L., Sakulyeva, T. N., & Bozhko, L. M. (2022). Supply chain risk management. *International Journal of Process Management and Benchmarking, 12*(6), 730–743. https://doi.org/10.1504/IJPMB.2022.125840
[12] El-Sayegh, S. M. (2021). Risk identification and assessment in sustainable construction projects in the UAE. *International Journal of Construction Management, 21*(4), 327–336. https://doi.org/10.1080/15623599.2018.1536963
[13] Gurtu, A., & Johny, J. (2021). Supply chain risk management: Literature review. *Risks, 9*(1), Article 16. https://doi.org/10.3390/risks9010016
[14] Habel, J., Alavi, S., & Heinitz, N. (2023). A theory of predictive sales analytics adoption. *AMS Review, 13*, 34–54. https://doi.org/10.1007/s13162-022-00252-0
[15] Haryudo, S. I., Anifah, L., Achmad, F., & Munoto. (2022). Project-based learning in the relationship of motivation and critical thinking to the competence of electrical engineering students. *Journal of Engineering Education Transformations, 36*(2), 178–184. https://doi.org/10.16920/jeet/2022/v36i2/22165
[16] Hosseinzadeh, N., & Hesamzadeh, M. R. (2012). Application of project-based learning (PBL) to the teaching of electrical power systems engineering. *IEEE Transactions on Education, 55*(4), 495–501. https://doi.org/10.1109/TE.2012.2191588
[17] Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. *Electronic Markets, 31*(3), 685–695. https://doi.org/10.1007/s12525-021-00475-2
[18] Khandakar, A., & Zainuddin, N. (2022). Case study of multi-course project-based learning and online assessment in electrical engineering courses during COVID-19 pandemic. *Sustainability, 14*(9), Article 5056. https://doi.org/10.3390/su14095056
[19] Lee, C., Cheang, P. Y. S., & Moslehpour, M. (2022). Predictive analytics in business analytics: Decision tree. *Advances in Decision Sciences, 26*(1), 1–30. https://doi.org/10.47654/V26Y2022I1P1-30
[20] Negi, A. (2021). Risk assessment and management in construction projects. *Mathematical Statistician and Engineering Applications, 70*(1), 668–675. https://doi.org/10.17762/msea.v70i1.2522
[21] Nabila, M. H., & Thompson, M. (2025). Countering foreign influence: The role of strategic communications in national security policy

making in the United States. *Sarcouncil Journal of Arts, Humanities and Social Sciences, 4*(09), 22–30. https://doi.org/10.5281/zenodo.17135544

[22] Panyukov, D. I., Kozlovskii, V. N., & Aidarov, D. V. (2023). Risk assessment and risk management. *Russian Engineering Research, 43*(8), 1011–1013. https://doi.org/10.3103/S1068798X23080208

[23] Rasul, N. (2021). Risk assessment of fast-track projects: A systems-based approach. *International Journal of Construction Management, 21*(11), 1–11. https://doi.org/10.1080/15623599.2019.1602587

[24] Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., Kording, K. P., Gomes, C. P., Ng, A. Y., Hassabis, D., Platt, J. C., Creutzig, F., Chayes, J., & Bengio, Y. (2022). Tackling climate change with machine learning. *ACM Computing Surveys, 55*(2), Article 42. https://doi.org/10.1145/3485128

[25] Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. *SN Computer Science, 2*(3), Article 160. https://doi.org/10.1007/s42979-021-00592-x

[26] , R. (2022). Integrating and transitioning the project front-end and project initiation phases in South African electrical engineering industrial projects. *International Journal of Managing Projects in Business, 16*(2), 1–26. https://doi.org/10.1108/IJMPB-04-2022-0094

[27] Tanwar, S. (2023). Machine learning. In *Computational Science and Its Applications* (pp. 13–42). Apple Academic Press. https://doi.org/10.1201/9781003347484-2

[28] Vasan, S. (2024, June). Addressing challenges and improving usability in UPI: Comprehensive study of digital payment systems. In *Sustainability and technology in the banking and insurance sector – challenges and opportunities* (pp. 37–58). IGI Global.

[29] Vasan, S. (2024, June). Addressing challenges and improving usability in UPI: Comprehensive study of digital payment systems. In *Sustainability and technology in the banking and insurance sector – challenges and opportunities* (pp. 37–58). IGI Global.

[30] Zavadskas, E. K., Turskis, Z., & Tamošaitienė, J. (2010). Risk assessment of construction projects. *Journal of Civil Engineering and Management, 16*(1), 33–46. https://doi.org/10.3846/jcem.2010.03

