IT Project Risk Prediction Framework: An AI-Based Approach

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Project Objective: Develop a predictive model to identify high-risk IT projects

Contents

Abstract

This report presents an AI-based framework for predicting IT project failure risk, developed using a synthetic dataset of 1,000 projects. The methodology encompasses data generation, preprocessing, exploratory data analysis (EDA), feature engineering, and machine learning modeling, with a focus on Random Forest and Logistic Regression. The threshold-adjusted Random Forest model achieved an accuracy of 0.7400 with a cross-validation accuracy of 0.7400 ± 0.0045, falling short of the 80% target, and exhibited a high-risk recall of 0.00. Key risk factors identified include project complexity and risk assessment variance. Recommendations include deploying the model for initial risk screening, integrating real-world data, and exploring advanced techniques such as SMOTE or Gradient Boosting to enhance performance. This work establishes a foundation for AI-driven risk management in IT projects.

1 Introduction

1.1 Background and Motivation

IT projects are pivotal to organizational success, yet they are prone to risks such as budget overruns, schedule delays, and scope creep. Industry reports, such as the Standish Group's CHAOS Report [1], indicate that approximately 30% of IT projects fail, while 50% face significant challenges. Proactive risk prediction can mitigate these issues, optimizing resource allocation and project planning.

1.2 Research Objectives

The objectives of this study are:

- To develop a predictive model for classifying IT projects as high-risk or low-risk.
- To identify and analyze key risk factors influencing project outcomes.
- To design a scalable framework for proactive risk management.

1.3 Success Metrics

The project targets:

- Model accuracy exceeding 80%.
- High recall for high-risk projects to ensure effective identification.
- Clear delineation of top risk factors through feature importance analysis.

2 Methodology

2.1 Data Generation

A synthetic dataset of 1,000 IT projects was generated to mimic real-world scenarios. Key attributes include:

- Project Characteristics: Team size (mean 10.73, maximum 55), planned duration (mean 275.57 days), planned budget (mean $2.33M, maximum $24.1M).
- Risk Factors: Technical, communication, requirement, vendor, and methodology risks, scored on a 1–10 scale.
- Outcomes: Budget overrun percentage, schedule delay percentage, scope delivered percentage, quality score, customer satisfaction, success rating, and high-risk status.

The dataset was balanced to include 25.3% high-risk projects, with a status distribution of 60.2% Successful, 37.8% Challenged, and 2% Failed.

2.2 Data Preprocessing

Preprocessing involved:

- Missing Values: No missing values detected.
- Duplicates: No duplicate records identified.
- Outliers: Detected in team size (6.2%), planned duration (5.3%), and planned budget (8.6%).
- Date Conversion: Converted start and end dates to datetime objects.
- Feature Creation: Added planned duration in months.

The cleaned dataset was saved as it_project_risk_data_cleaned.csv.

2.3 Exploratory Data Analysis (EDA)

EDA findings include:

- Distributions: Right-skewed distributions for team size, duration, and budget, with maximum values deemed realistic.
- Correlations: Weak correlations with high-risk status (maximum 0.132 for complexity).
- Visualizations: Generated histograms, a status distribution pie chart, a risk distribution bar plot, and a correlation heatmap.

2.4 Feature Engineering

New features were engineered to boost model performance:

- Composite Risk Score: Average of all risk factors.
- Budget per Team Member: Planned budget divided by team size.
- Duration-Complexity Factor: Product of duration and complexity, normalized by 100.
- Risk Assessment Variance: Variance across risk factors.
- Experience-Complexity Gap: Difference between complexity and client experience.

- Categorical Features: Binned budget, duration, and team size into categories (e.g., Low, Medium, High).

The engineered dataset was saved as it_project_risk_data_engineered.csv.

2.5 Model Development

Initial models included:

- Logistic Regression: Achieved 73.00% accuracy with a high-risk recall of 0.04.
- Random Forest: Achieved 75.00% accuracy with a high-risk recall of 0.02.

The Random Forest was enhanced with:

- Class Weights: Set to ”balanced” to address the 25.3% high-risk class.
- Hyperparameter Tuning: Optimized max_depth (None) and min_samples_split (2).
- Threshold Adjustment: Reduced to 0.3 to prioritize high-risk recall.

2.6 Model Evaluation

The threshold-adjusted Random Forest yielded:

- Accuracy: 0.7400
- Cross-Validation Accuracy: 0.7400 ± 0.0045
- High-Risk Recall: 0.00
- ROC-AUC: 0.67

Confusion matrices and ROC curves were generated for analysis.

3 Results

3.1 Model Performance

The threshold-adjusted Random Forest achieved:

- Accuracy: 74.00%, below the 80% target.
- High-Risk Recall: 0.00, indicating no high-risk projects were correctly identified.
- Precision (High-Risk): 0.00 (no positive predictions).
- F1-Score (High-Risk): 0.00.

The model excels at identifying low-risk projects (recall 0.99) but fails with high-risk cases.

3.2 Key Risk Factors

Top five risk factors from feature importance:

1. Complexity (0.0555)
2. Risk Assessment Variance (0.0553)
3. Planned Budget (0.0535)
4. Client Experience (0.0534)
5. Methodology Risk (0.0532)

3.3 Visualizations

Key visualizations include:

- Confusion Matrix: Highlights high true negatives but no true positives.
- ROC Curve: AUC of 0.67, indicating moderate discriminative ability.
- Feature Importance: Bar plot of top 10 features.

4 Discussion

4.1 Performance Analysis

The 74% accuracy and 0.00 high-risk recall indicate underperformance. Key issues include:

- Class Imbalance: The 25.3% high-risk class is insufficiently addressed.
- Feature Weakness: Low correlations (max 0.132) and importance scores (0.05) limit predictive power.
- Threshold Limitation: Adjusting to 0.3 did not improve recall, suggesting deeper feature issues.

4.2 Limitations

- Synthetic Data: May lack real-world nuances.
- Feature Scope: Additional features (e.g., stakeholder engagement) could enhance prediction.
- Model Selection: Random Forest may not be optimal; alternatives like Gradient Boosting could be explored.

4.3 Future Directions

- Real Data Integration: Incorporate real-world project data.
- Advanced Techniques: Apply SMOTE, Gradient Boosting, or neural networks.
- Feature Optimization: Use feature selection methods like recursive elimination.

5 Conclusions

This study developed a proof-of-concept for IT project risk prediction. Despite not meeting the 80% accuracy goal, it identifies critical risk factors (e.g., complexity, risk variance). The framework offers a foundation for proactive risk management, with significant potential for improvement through real data and advanced modeling.

6 Recommendations

- Deployment: Use the model for initial risk screening, focusing on complexity and risk scores.
- Data Collection: Gather real-world IT project data for enhanced training.
- Model Enhancement: Explore SMOTE, Gradient Boosting, or neural networks.
- Monitoring: Implement a feedback loop to update the model with new project outcomes.

Appendices

Appendix A: Dataset Description

Statistic	Value
Number of Projects	1,000
Number of Features	29
Team Size (Mean)	10.73
Team Size (Max)	55
Planned Budget (Mean)	$2.33M
Planned Budget (Max)	$24.1M
High-Risk Percentage	25.3%

Table 1: Dataset Statistics

Appendix B: Model Parameters

Parameter	Value
Estimators	100
Max Depth	None
Min Samples Split	2
Class Weight	Balanced
Threshold	0.3

Table 2: Model Parameters

References

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