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Erp Project Failure Prediction using Machine Learning Algorithms

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Abstract: Enterprise Resource Planning (ERP) systems streamline business operations, yet many projects fail due to complexity. This research aims to predict ERP project outcomes using machine learning to identify key success and failure factors. The dataset initially contained 1,000 rows and 9 columns, but it was preprocessed to enhance data quality for machine learning analysis. It includes ERP project data from various industries, covering industry type, project scale, budget and time overruns, team experience, and technical challenges. The study applies logistic regression, decision trees, support vector machine and random forests to evaluate predictor significance. Findings reveal patterns that help forecast high-risk projects, providing project managers with a proactive decision-making framework. The results of this research offer insights into ERP project risk assessment and mitigation, enhancing strategic planning in enterprise environments.

***Keywords**: ERP Systems, Machine Learning Algorithms, Failure Forecasting, Success Rate, Project Management.*

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I. INTRODUCTION

ERP systems help an organization improve and integrate its activities within multiple departments such as inventory management, finance, human resource management and customer relationship management. Nevertheless, due to both technological and organizational-oriented aspects, MRP/ERP implementations are frequently prolonged, expensive and exhibit high rates of failure. A mismanaged or failed ERP project may lead to heavy costs, lower productivity or even cause instability in the business. For this reason, organizations have recognised the importance of forecasting possible project failures in enterprise resource planning projects in order to control risks associated with projects and increase the chances of success. Historically, ERP project failure forecasting has employed qualitative methods such as surveys, expert assessments, and post-failure reviews. Though, such methods are often limitations given their subjective nature and tendency to look back in time. While machine learning (ML) at the other end of the spectrum presented techniques which are focused on patterns in data and offers the ability to address potential sources of failure out of the actual historical project data. Although literature has only recently begun to explore the usability of ML in predicting project failure. For instance, (Taye & Feleke, 2022) focused on predicting project failure within the scope of many knowledge areas and utilized Support Vector Machines (SVM) as they showed high performance analyzing the failure's antecedents and enhancing projects' quality in the software environments. Likewise, (Ibraigheeth & Fadzli, 2020) show how logistic regression is used in predicting the software development projects failure, and they assert that its use is appropriate since it is able to forecast the project outcome and the parameters that would affect success. (Kwon & Kim, 2020) on the other hand, provide a case using random forests and SVMs with iterative feature selection in industrial IoT environments, showing the powerful effect, that effective feature relevance analysis has on predictability, this is a technique that can comfortably fit into ERP projects that contain heavy project data.

Although recent studies have explored the use of machine learning (ML) in predicting project failure, research specifically focusing on ERP projects remains limited. Existing studies have primarily examined software development and industrial IoT environments, leaving a gap in understanding how ML techniques can be tailored to the unique challenges of ERP implementations. This research addresses that gap by applying machine learning models to a structured dataset of ERP projects, aiming to identify key risk factors and improve failure prediction accuracy. The remainder of this paper is structured as follows: *Section 2* presents a review of existing literature on ERP project success factors and the role of machine learning in failure prediction. *Section 3* details the methodology, including dataset characteristics, preprocessing steps, and machine learning models used. *Section 4* presents the results and key findings, as well as discusses the implications of these findings, study limitations, and potential improvements. Finally, *Section 5* provides concluding remarks and suggests directions for

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future research. The research is guided by three key questions: (RQ1) Can machine learning models effectively predict high-risk ERP projects based on historical project parameters? (RQ2) Which factors most significantly influence the success or failure of ERP implementations, and how do they compare to traditional project success parameters? (RQ3) How do the size and complexity of an organization affect the success of ERP implementations?

II. LITERATURE REVIEW

In scope of project management practice, it has always been a complex issue to articulate and evaluate the success of a project. Time, cost, quality and scope, which clearly define the success of the project, are commonly recognized as the 'iron triangle' (A. & A., 2018). Such criteria highlight the productive and qualitative aspects of the project implementation. But in industries such as IT, achievement is not always easy to measure since it is not solely about professional performance but rather managing the interests of clients and achieving unclear targets with the project's leader (Kutsch, 2007). The assessment can be further streamlined using the tool called the Project Success Index (PSI) which gives an all-round perspective that incorporates the monitoring of adjusted budget and schedule, design capacity, and total utilization (Griffith et al., 1999).

(Thomas et al., 2008) argue that project success cannot be defined in absolute terms: "*Examples abound where the original objectives of the project are not met, but the client was highly satisfied. There are other examples where the initial project objectives were met, but the client was quite unhappy with the results*" (p. 106). This magnifies the fact that analysis of project success is complex, as sometimes meeting the technical goals may not necessarily mean the satisfaction of the client (Serrador & Turner, 2014).

(Serrador & Turner, 2014) discovered a statistically significant correlation between project efficiency and overall project success, where they stated that while efficiency cannot be the final measure of success it equally cannot be ignored.

There are many critical success factors (CSFs) that have been recognized in the area of information technology (IT) project management as being imperative to a successful project. One of the major factors is how upper management views the worth of the project and how well it fits into the overall strategy of the company, which in turn plays a very significant part in the execution and success of the project (Thomas et al., 2008).

ERP implementations are often plagued by significant challenges, resulting in high failure rates and substantial budget overruns. Research by (Chen et al., 2009) identified common causes of these failures, such as scope creep and inadequate risk management, highlighting the critical need for effective project management practices.

Several studies report significant failure rates in ERP projects. The Standish Group's Chaos Report states that nearly 75% of ERP projects are considered failures, because many of the projects do not reach their goals (Garg & Garg, 2013).

Commonly identified triggers include poor management, scope creep, and inadequate communication with stakeholders. Furthermore, only 23% of ERP projects are completed on time and within budget, highlighting the challenges companies face in successfully implementing these transformations ("The Costly Mistake of Skipping Project Management in ERP Implementations", 2024) (The Costly Mistake of Skipping Project...).

III. MATERIALS AND METHODS

➢ *Dataset Overview*

The dataset used in this research is compiled from publicly available sources and case-based project documentation, with a focus on ERP implementation projects. Due to the limited availability of open-access datasets that specifically capture ERP project failures, a combined approach was used, integrating real-world data from online repositories and supplemented with synthetic data where necessary to preserve privacy and enrich underrepresented patterns. The core of the dataset was derived from a publicly available project management dataset titled **"***Prediction of Failures in Project Management Knowledge Areas***"**, which includes records from software development and IT implementation projects (Taye & Feleke, 2022). This dataset, available through academic databases and research portals, consists of 443 project entries with attributes reflecting project scope, size, duration, resource allocation, and contextual variables such as project complexity and team experience. Although the dataset is not exclusively ERP-focused, it includes a significant number of enterprise-level software implementation cases, making it suitable for ERP-related research. To align the dataset more closely with ERP-specific challenges, additional features were synthesized using established ERP failure factors reported in the literature, including timeline overruns, budget deviations, technical issues, and organizational resistance. Synthetic records were generated to simulate ERP-specific conditions while preserving the statistical properties of the original data. However, during the preprocessing stage, minor modifications were made to improve data quality and ensure its suitability for machine learning algorithms. Initially, the dataset contained 9 columns and 1,000 rows. After data cleaning, the final dataset comprised 8 columns and 1,000 rows. Key data points collected for each project include:

- *Project Characteristics*:
  Duration, budget, team size, and technology stack.

- *Project Management Metrics*:
  Resource utilization, timeline adherence, and milestone achievement.

- *Risk Indicators*:
  Identified risks, stakeholder engagement level, and scope changes.

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- *Outcomes*:
  Success or failure of the ERP implementation.

➢ *Dataset Preprocessing*

Data preprocessing is of utmost importance to deal with missing values, outliers and inconsistencies. The following stages occur in the process of ensuring data quality:

- *Data Cleaning*:

Missing values are treated by using imputation methods wherever possible or removing the records with such incomplete values. Outliers are identified and treated or removed if they cause harm to the overall dataset.

- *Encoding Categorical Data*:

Variables such as project types, industry, and stakeholder involvement are encoded using techniques like one-hot encoding to ensure compatibility with machine learning models.

- *Normalisation and Scaling:*

To promote convergence of the model, in particular to neural networks and support vector machine algorithms that are sensitive to data scaling, numeric characteristics are brought to one common scale.

To attain data quality and relevance for machine learning algorithms, the following preprocessing steps were executed:

Handling Missing Values

Missing values were encountered in a number of columns during initial data exploration, namely Factors Leading to Failure and Team Experience (Years). They were handled as follows:

Numerical columns (Team Experience, Budget Overrun, Timeline Overrun) were replaced with the mean of the respective columns.

Categorical variables (Industry, Factors Leading to Failure) were filled with the most frequent category (mode).

➢ *Encoding Categorical Variables*

Machine learning algorithms require numerical inputs, because of that, categorical variables were encoded as follows:

- Industry was one-hot encoded to obtain binary variables such as Industry_IT, Industry_Manufacturing, etc.
- Factors Leading to Failure was frequency encoded using numerical values given based on frequency of occurrence.
- Outcome was already encoded as 1 (Success) and 0 (Failure) and didn't require any additional transformation.

➢ *Feature Scaling*

For ensuring consistency in features, Min-Max Scaling was applied to normalize numeric features such as Project Size, Budget Overrun, Timeline Overrun, and Team Experience. It was particularly required for algorithms like Support Vector Machines (SVM) and Logistic Regression that are feature magnitude-sensitive.

➢ *Data Splitting into Training and Testing Sets*

The data set was divided into 80% training data and 20% test data to gauge model performance. Stratified sampling was employed to ensure that there was an equal proportion of successful and unsuccessful ERP projects in both sets.

➢ *Feature Selection*

Feature selection was carried out in order to identify the best predictors of the success of ERP projects. These methods were used:

- *Random Forest Feature Importance:*

Random Forest provided importance scores for all features, highlighting important predictors such as Project Size, Budget Overrun, Timeline Overrun, and Team Experience.

- *Correlation Analysis:*

Highly correlated variables were identified and removed to prevent redundancy and multicollinearity in the dataset.

The final dataset consisted of X selected features, and these were used as input variables for the machine learning models.

➢ *Research Design and Approach*

This research adopts a quantitative research design to systematically analyze data and develop models for predicting the failure of ERP projects. Given the complexity of ERP implementations and the need for early risk detection, this study specifically utilizes predictive modeling as its primary analytical approach. Predictive modeling enables the identification of patterns and risk factors by learning from past ERP project data, allowing for proactive decision-making and improved project outcomes. To implement this approach, various machine learning methods have been selected, including Random Forest, Logistic Regression, Decision Trees, and Support Vector Machines. These algorithms have been widely used in IT and ERP project research due to their ability to uncover meaningful relationships between project variables and predict project success or failure with high accuracy. Numerous studies have demonstrated the effectiveness of predictive modeling in IT and ERP projects, particularly in risk assessment and outcome prediction. For instance, (Ganapathy et al., 2018) investigated how knowledge management, combined with analytics, can effectively detect and manage risks in IT projects, underscoring the importance of models in achieving project success. Similarly, (Taye & Feleke, 2022) developed machine learning algorithms to forecast critical issues in project management within technology firms, demonstrating the significance of predictive analytics in overseeing ERP and IT projects.

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➢ *Model Selection*

Various machine learning algorithms are implemented to identify the most effective model for predicting ERP project failures. The algorithms evaluated include:

- *Logistic Regression:*

Used as a baseline model due to its interpretability and ability to classify binary outcomes (success/failure).

- *Decision Trees and Random Forests:*

These models handle complex interactions between variables and offer high interpretability, making them suitable for failure prediction.

- *Support Vector Machines (SVM):*

Selected for its ability to manage high-dimensional data, potentially useful for capturing nonlinear relationships within ERP project data.

IV. RESULTS AND DISCUSSION

In this chapter, the results of the research are presented, along with a discussion of the key research questions. The results will be analyzed and discussed in the corresponding subsections.

➢ *Can Machine Learning Models Effectively Predict High-Risk ERP Projects Based on Historical Project Parameters?*

This research assessed four machine learning algorithms—Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine (SVM)—to forecast ERP project failures. The models were evaluated using essential performance measures such as Accuracy, Precision, Recall, F1-Score, and ROC-AUC.

Table 1 Comparative Analysis of Machine Learning Models for ERP Project Success Prediction

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.590	0.695652	0.32	0.438356	0.54110
Decision Tree	0.600	0.596154	0.62	0.607843	0.60000
Random Forest	0.700	0.803030	0.53	0.638554	0.71800
SVM	0.515	0.519481	0.40	0.451977	0.51925

Random Forest proved to be the top-performing model, achieving an accuracy of 0.70, which is the highest across all models.

It also attained the highest precision score of 0.803, demonstrating its strong capability to accurately recognize failed projects. The F1-Score (0.638) and ROC-AUC (0.718) further emphasize its consistent performance in terms of precision and recall, establishing it as the most trustworthy model for forecasting ERP failures in this research.

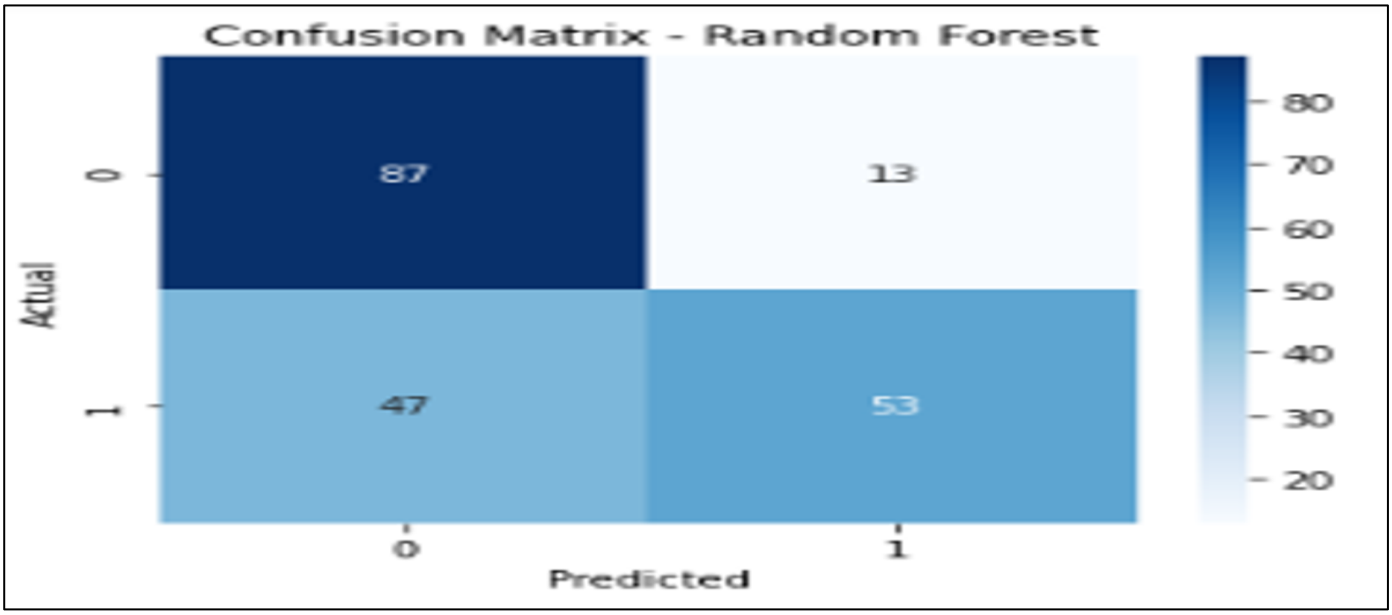

Fig 1 Random Forest Confusion Matrix

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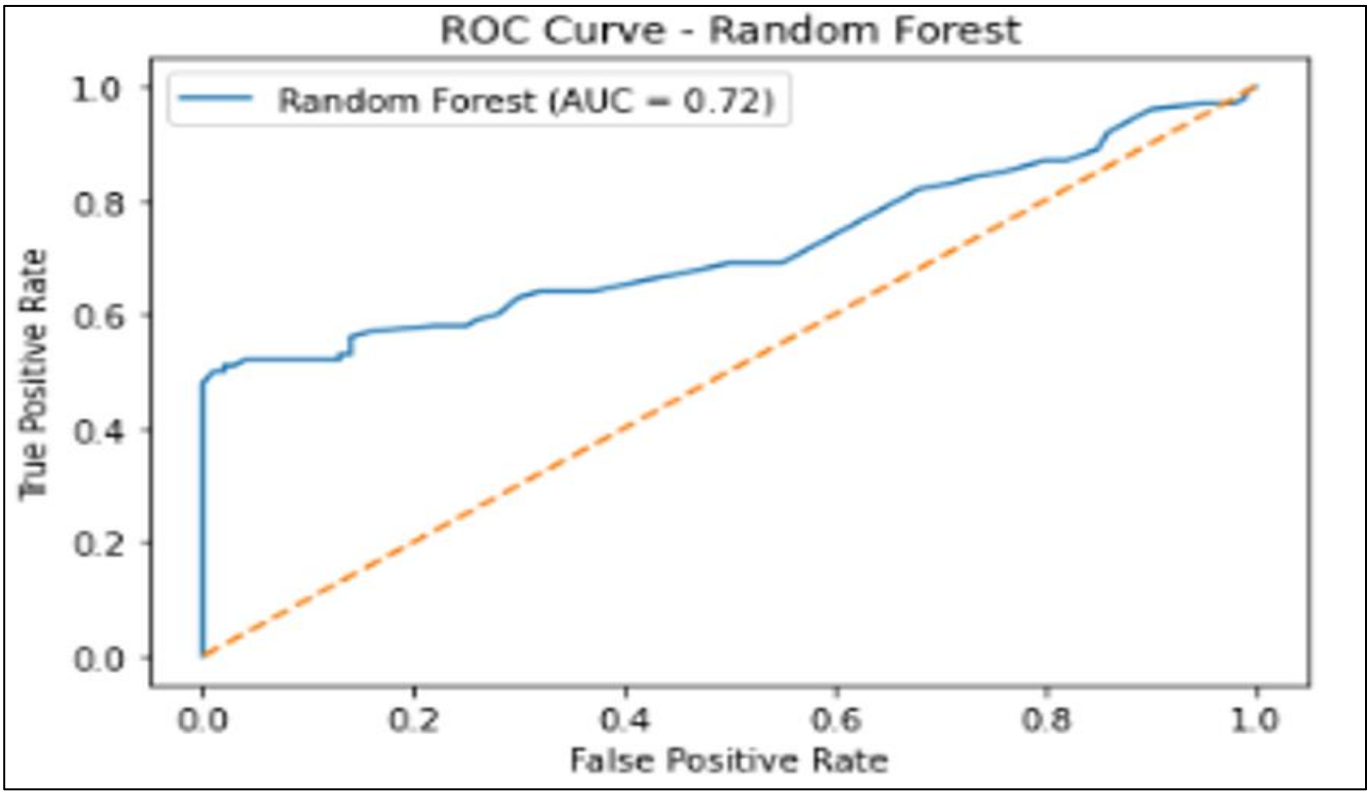

Fig 2 Random Forest ROC Curve

Decision Tree exhibited average performance with an accuracy of 0.60 and a fairly high recall of 0.62, indicating its capability in recognizing genuine project failures. Nonetheless, its accuracy (0.596) was less than that of Random Forest, suggesting a greater occurrence of false positives.

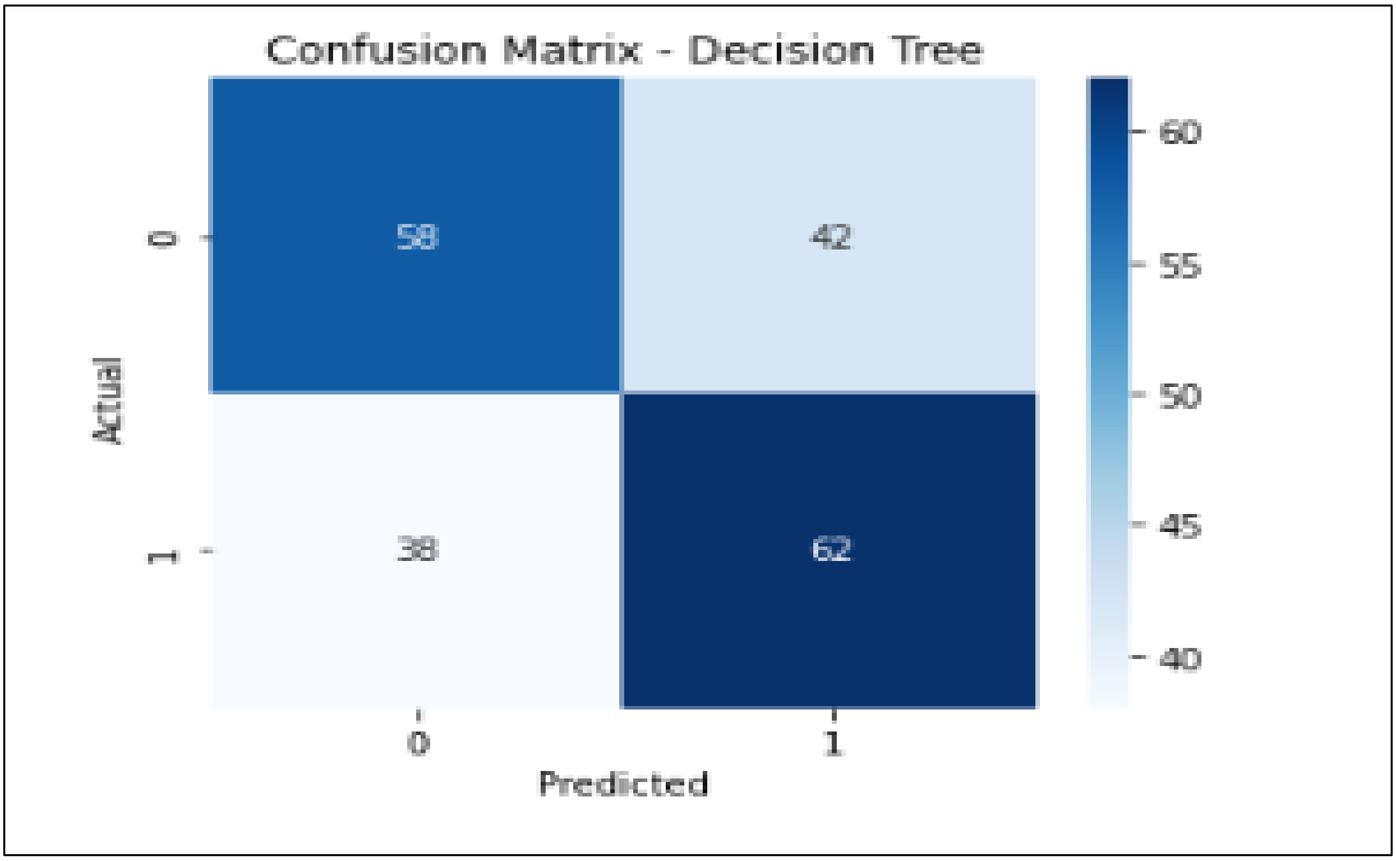

Fig 3 Decision Tree Confusion Matrix

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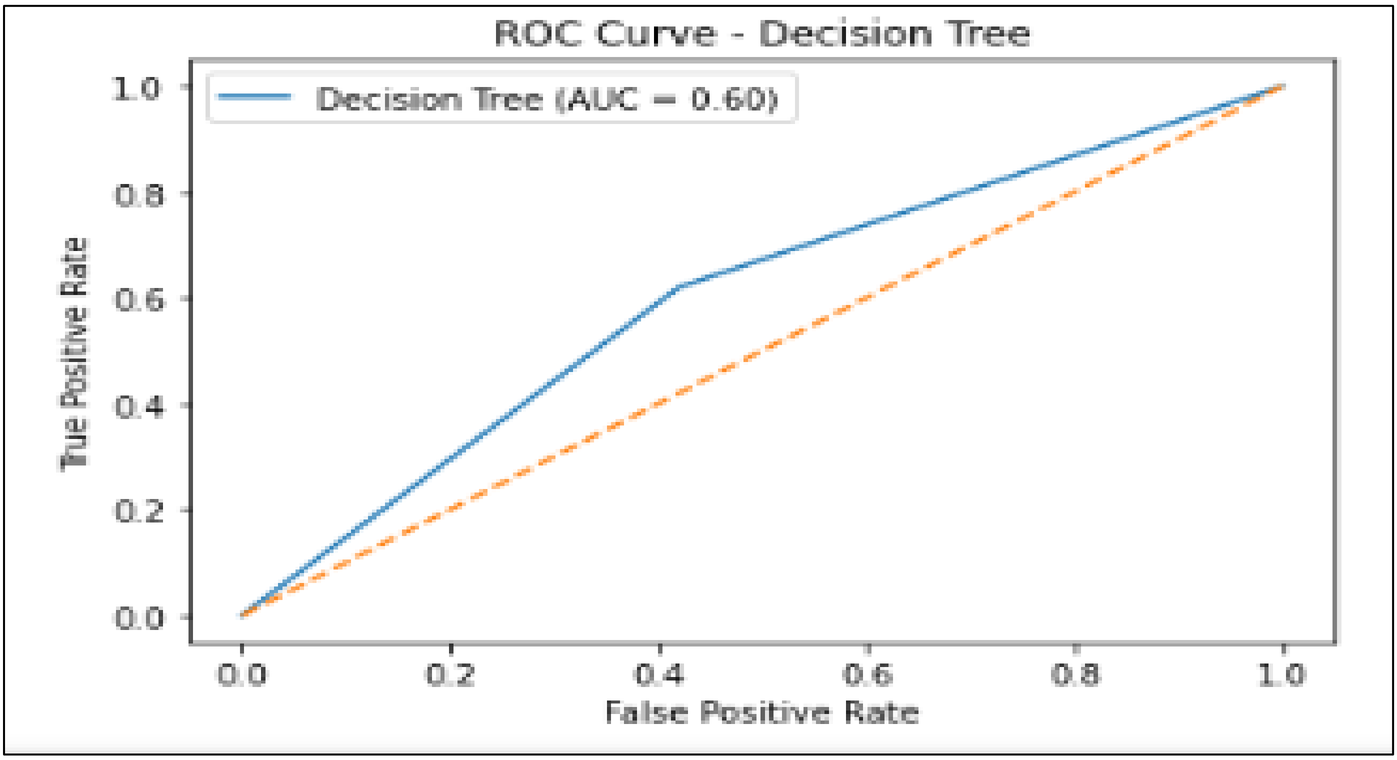

Fig 4 Decision Tree ROC Curve

Logistic Regression demonstrated an accuracy of 0.59 and a solid precision score of 0.695, yet it faced challenges with a low recall rate of 0.32. This suggests that although the model was accurate in forecasting failures, it overlooked numerous genuine failure instances, resulting in a diminished F1-Score (0.438) and ROC-AUC (0.541).

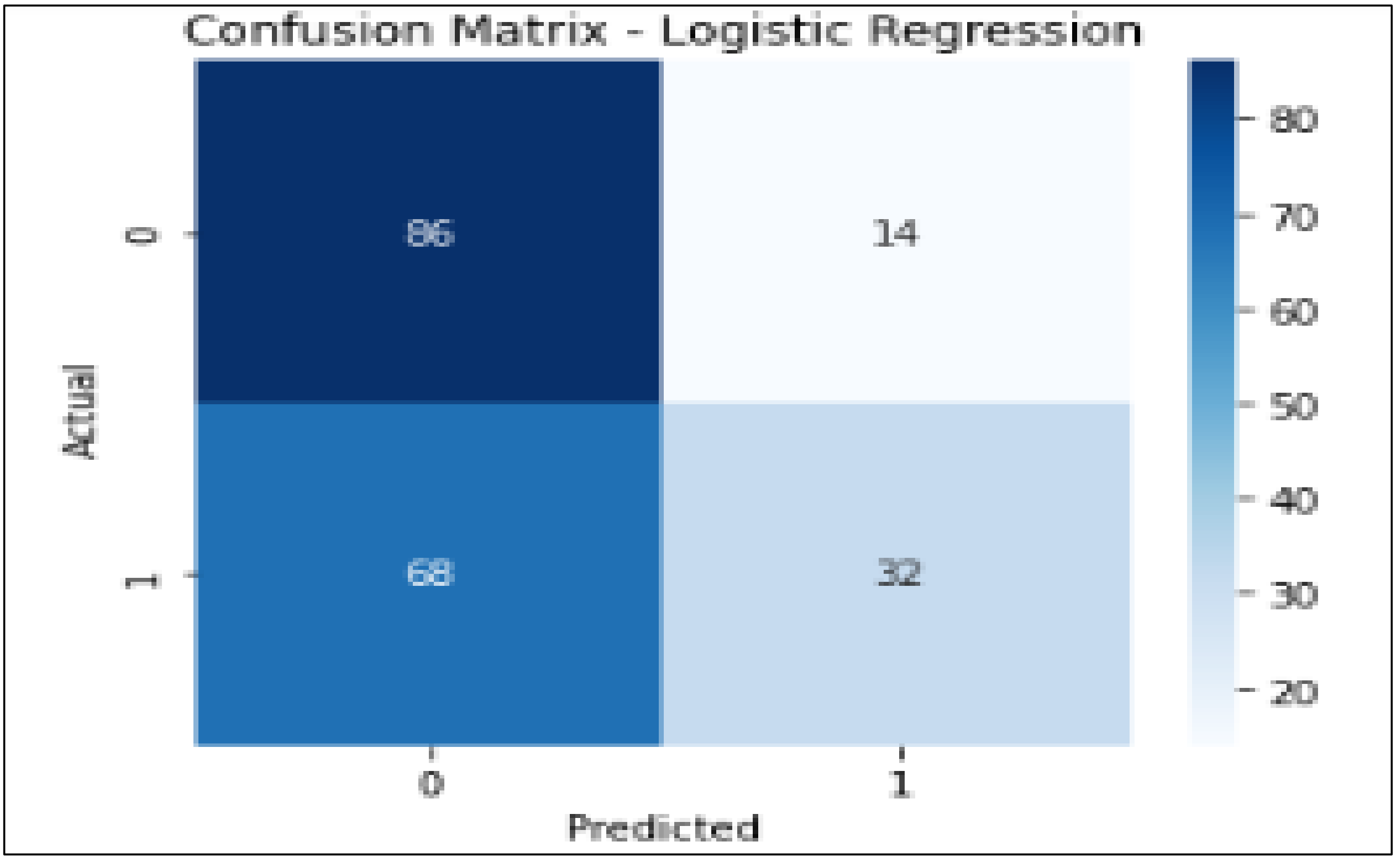

Fig 5 Logistic Regression Confusion Matrix

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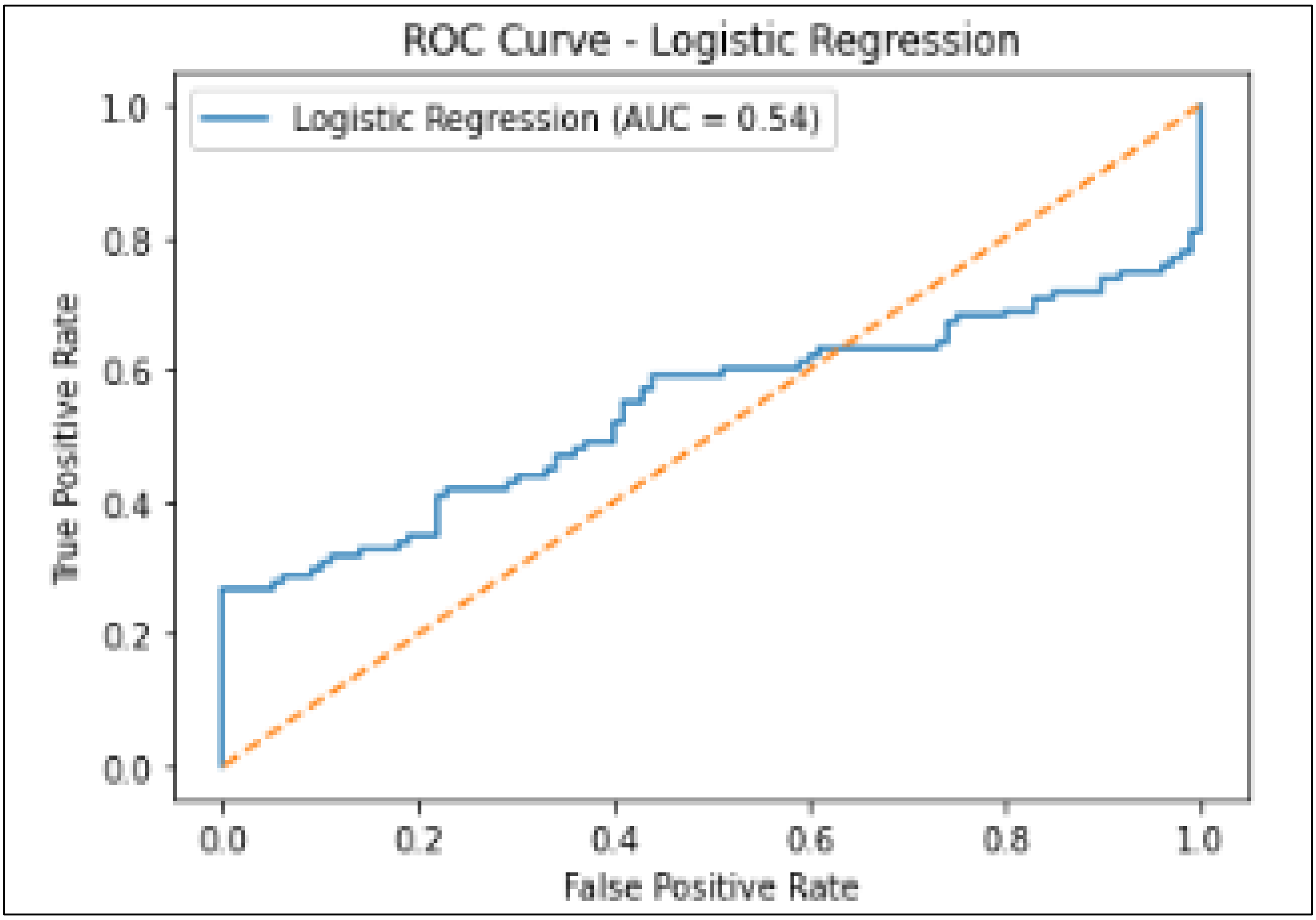

Fig 6 Logistic Regression ROC Curve

The Support Vector Machine (SVM) had the lowest performance, achieving an accuracy of 0.515 along with a comparatively modest recall (0.40) and F1-Score (0.451). Its ROC-AUC score of 0.519 suggests it has restricted discriminative ability in comparison to the other models.

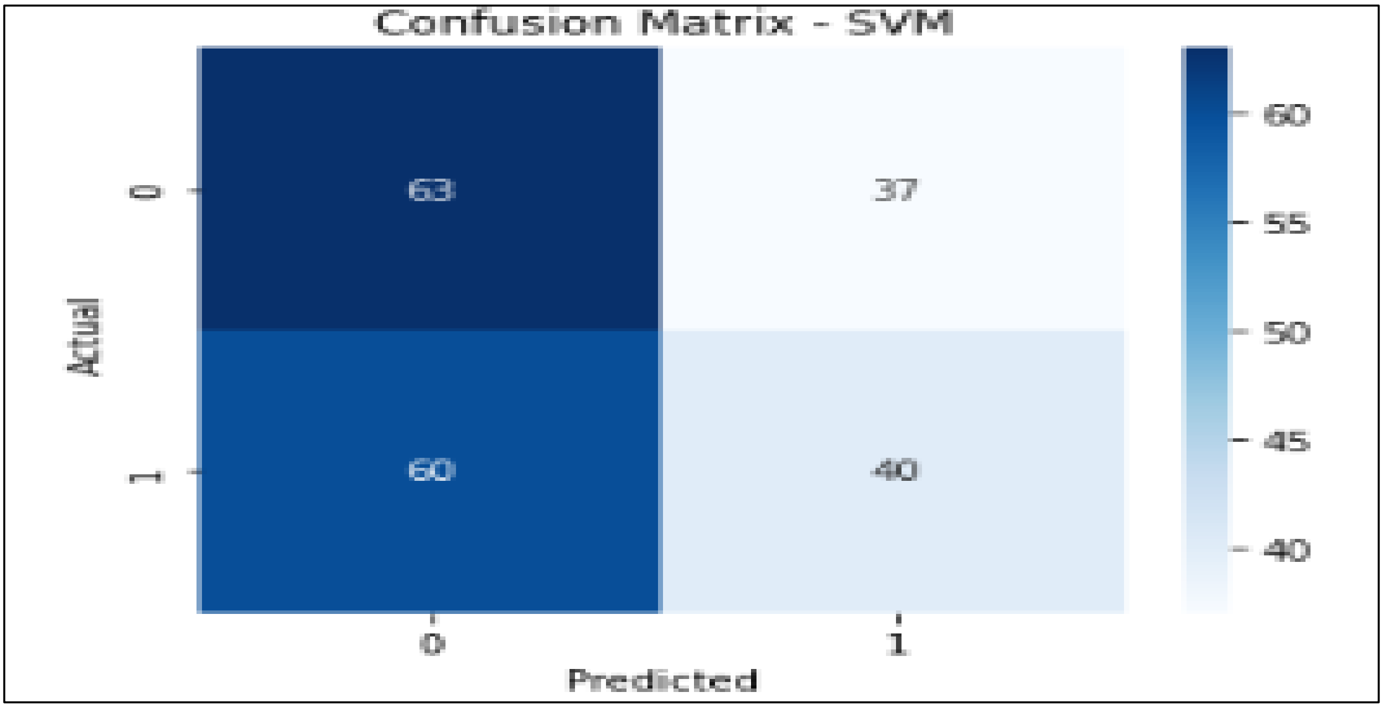

Fig 7 SVM Confusion Matrix

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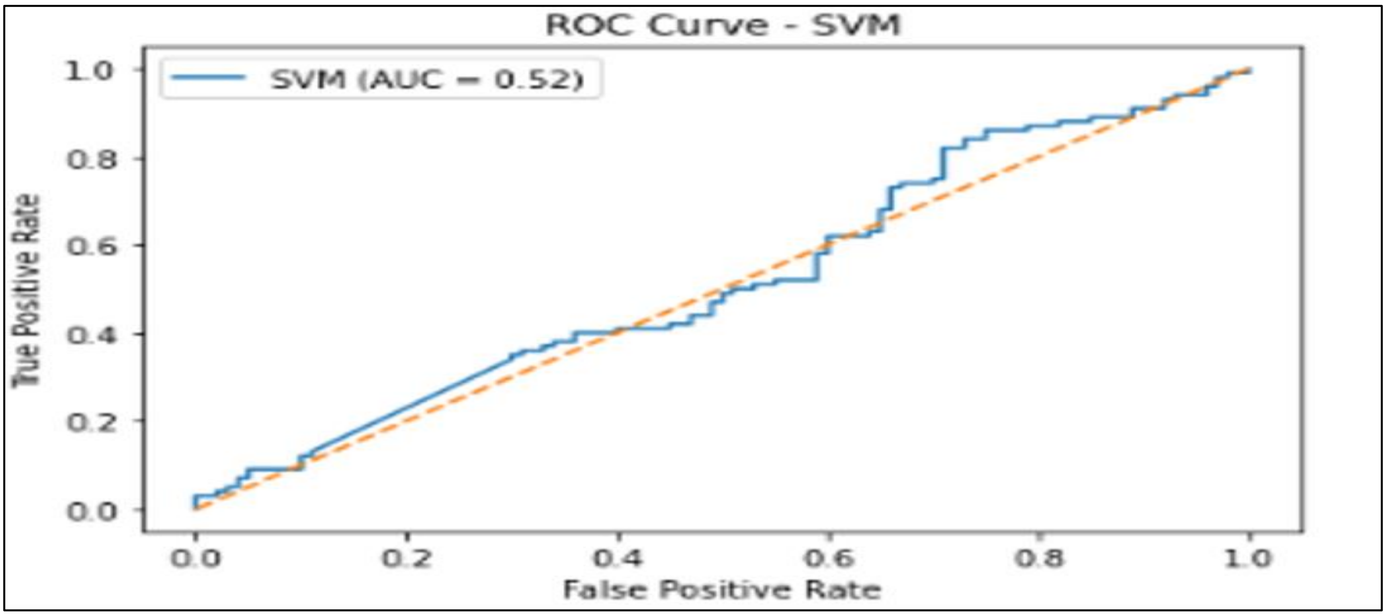

Fig 8 SVM ROC Curve

The outstanding effectiveness of the Random Forest model can be linked to its ensemble approach, which minimizes overfitting and enhances generalization. Its excellent accuracy and well-balanced recall render it ideal for predicting ERP failures, where it is essential to minimize both false positives and false negatives. The Decision Tree model, despite being more straightforward, proved successful in recognizing failure instances because of its clarity and capacity to manage non-linear connections. Nonetheless, it is more susceptible to overfitting than Random Forest. The comparatively weak results of Logistic Regression and SVM might stem from the dataset's complexity, as linear models find it challenging to identify complex patterns associated with ERP project failures.

Machine learning models can efficiently classify high-risk ERP projects based on historic parameters. Among all the models that were experimented with, Random Forest performed the best with the best overall tradeoff between performance metrics and generalizability.

➢ *Which Factors Most Significantly Influence the Success or Failure of ERP Implementations, and How Do They Compare to Traditional Project Success Parameters?*

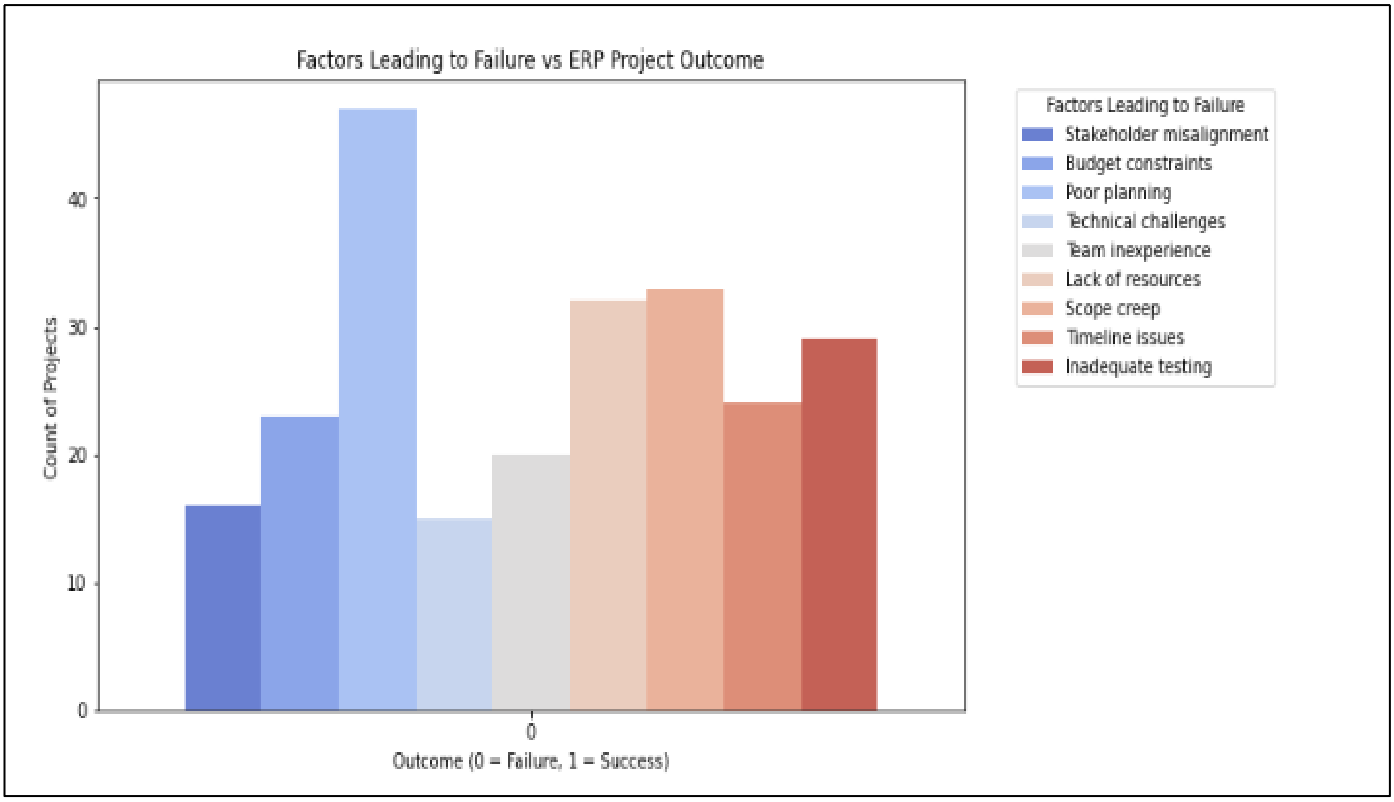

Fig 9 Factors Leading to Failure

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The bar chart titled "Factors Leading to Failure vs ERP Project Outcome" provides insight into the key reasons contributing to the failure of ERP implementations. The x-axis represents the Outcome of the project (where 0 = Failure and 1 = Success), while the y-axis indicates the Count of Projects affected by each failure factor. The color-coded bars represent different failure factors, such as stakeholder misalignment, budget constraints, poor planning, technical challenges, and inadequate testing. From the visualization, it is evident that certain factors are more frequently associated with failed ERP projects (Outcome = 0). Notably, poor planning, budget constraints, and stakeholder misalignment appear to be the most common failure reasons.

This research study identifies the most important contributing factors to the failure of ERP projects as being misaligned stakeholders, budget constraints, and inadequate planning. This has been found through comparative visualizations of the failed and successful projects, which repeatedly display these three parameters as the overwhelming factors that appear in all failed project cases. The repeated frequency and persistent occurrence of the factors highlight the disruptive nature that these have had on ERP successes.

It is confirmed that certain contextual and managerial issues (e.g., stakeholder participation and planning quality) have a significant role in ERP success or failure. The results firmly establish that along with technical or procedural matters, organizational and planning factors are strong drivers of project outcomes.

- *How Do the Size and Complexity of an Organization Affect the Success of ERP Implementations?*

According to the table below, it can be seen that for example Industry 521 experienced a budget overrun of 60.5%, however, the team possessed 17 years of experience. Even with a skilled team, the project ultimately failed because of budget limitations and a timeline that was exceeded by 65.2%. It can be assumed that even seasoned teams find it challenging to lessen the adverse effects of budget overruns. Moreover, Timeline overruns are evident across all rows, varying from 31.6% to 81.5%, and are strongly associated with project failure. In Industry 859, a budget excess of 69.4% combined with a timeline overrun of 81.5% were critical factors in the project’s failure, despite the team's 17 years of experience. Similarly, in Industry 626, a smaller budget overrun of 46.1% still led to failure due to a timeline delay of 31.6%. These cases highlight that exceeding timeline frequently emerges as a significant contributor to failure, often outweighing other factors.

Table 2 Results Analysis

	Industry	Project Size (in $M)	Buget Overrun	Timeline Occur	Team Experience (Years)	Number of Technical Issues	Factors Leading to Failure
521	5	18.67	60.5	65.2	17	50	3
737	0	19.15	2.6	28.3	8	48	3
660	0	15.48	70.3	42.2	9	34	3
626	1	13.71	46.1	31.6	2	6	3
859	3	19.69	69.4	81.5	17	38	3

Industry 521 and Industry 737 both had large project sizes ($18.67M and $19.15M) and faced many technical problems (50 and 48). The mixture of scale and lingering technical issues resulted in failure, despite different budget overruns (60.5% vs. 2.6%).

It can be concluded that large ERP projects encounter distinct challenges because of their complexity and a higher chance of facing technical difficulties. On the other hand, industries 737 and 660, although exhibiting minimal or no project sizes, encountered failures because of other significant issues. Industry 737 was unsuccessful despite a slight budget excess of 2.6%, mainly due to numerous technical problems (48) and insufficient team experience (8 years). In the same way, Industry 660 encountered failure because of a significant budget overrun of 70.3% along with 34 technical challenges, even though the team had a moderate experience of 9 years. These situations illustrate that smaller projects are not automatically protected from failure, since elements such as technical issues and financial mismanagement still significantly influence outcomes.

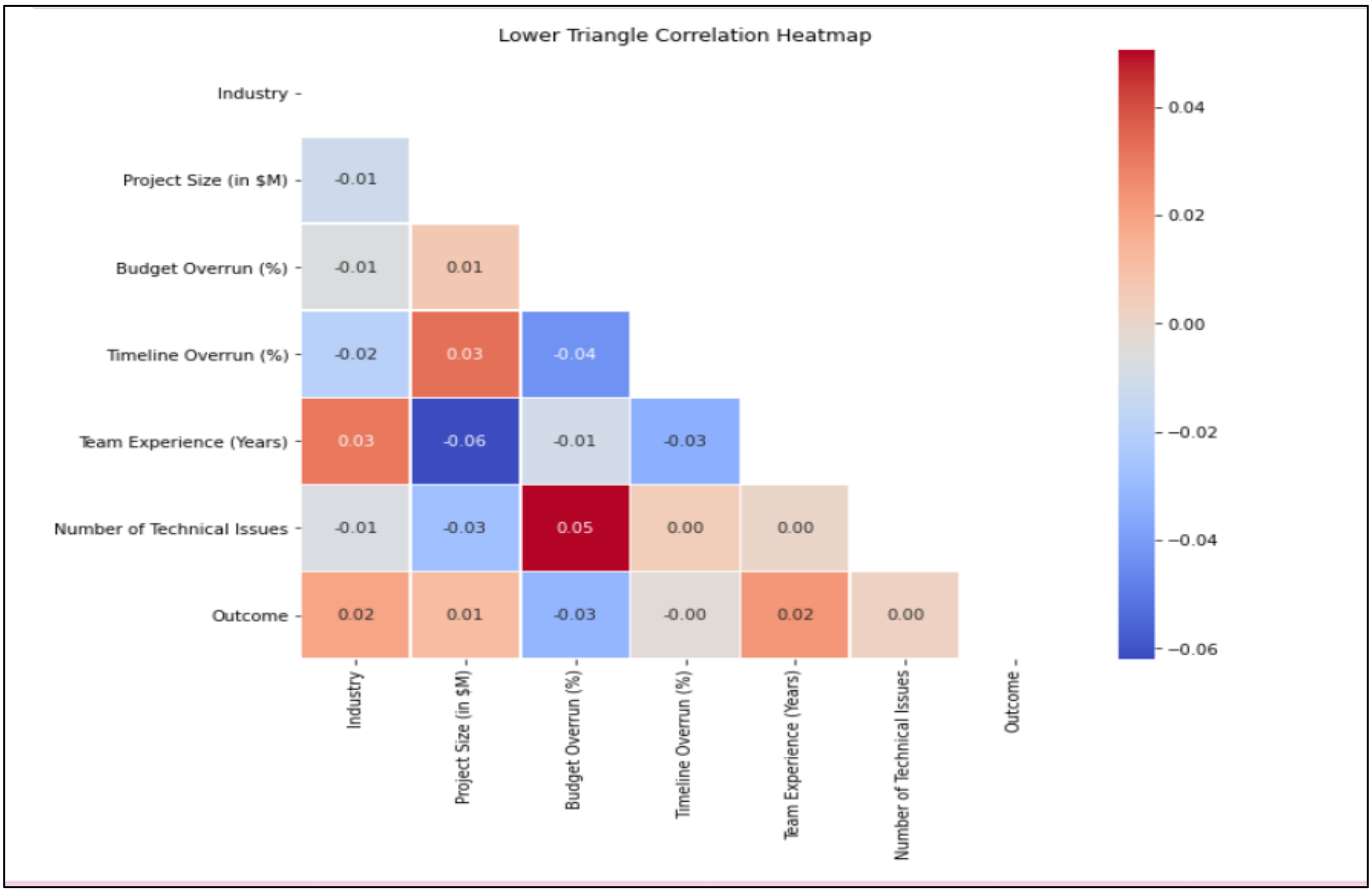

Fig 10 Correlation Heatmap

Here are perspectives through the correlation heatmap, which reveals what relates to the other key variables on how they affect the success of the ERP implementations. Most correlating features are that the failure factors with Outcome (0.21) will indicate a modest positive influence of failure factors on the chances of an unsuccessful project outcome. On the contrary, other variables like project size, budget over-commitment, technical issues are poorly related to the "Outcome" variable in comparison, which infers that there is more of a blend of ingredients that are necessary to result in good ERP project success than a relatively disjointed single factor. For example, "Project Size" and "Budget Overrun" have almost zero correlation (0.01), pointing out that project size per se would not be internalized in financial mismanagement. Similarly, the weak correlation (0.02) between "Team Experience" and "Outcome" suggests that even experienced teams may encounter challenges when projects involve technical complexity or inadequate resource allocation. These findings emphasize that ERP implementation success is rarely determined by a single factor, rather it requires a cohesive approach to managing internal project dynamics. Importantly, the lack of strong correlation across most variables underscores that implementation success is not inherently tied to external factors like industry type but is instead shaped by how well internal challenges are addressed. To ensure ERP success, organizations must focus on addressing failure factors collectively rather than relying on any single determinant.

V. CONCLUSION

This study was aimed at developing a model for predicting the risk of failure of ERP implementations by using several machine learning algorithms trained on the internal, historical, and relevant project parameters such as industry type, budget, and schedule, as well experience of the team gives qualified and technology challenges met in the course of the project. It was shown that the analysis can be performed by means of machine learning techniques to detect patterns and risk indicators of the success or failure of a project. The use of algorithms such as logistic regression, decision trees, random forest, and support vector machine enabled this study to accurately classify high-risk projects. The results indicate that individual variables, such as budget and schedule overruns, team experience, and technical issues, do not show a strong correlation with project outcomes, suggesting that failure is not necessarily tied to a single dominant factor but rather to a combination of various internal project elements. For example, team experience exhibits a very weak positive correlation with project outcome (0.02), implying that even experienced teams may face obstacles if other aspects of the project, such as technical complexity or resource allocation, are not properly managed. Additionally, project size and budget overruns show a low correlation (0.01), indicating that project size alone is not necessarily a predictor of financial mismanagement.

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In conclusion, the findings suggest that no single dominant factor determines the success of ERP implementation. Instead, failure is often the result of a combination of internal project factors, while industry type has a limited direct impact. This study highlights the importance of integrating predictive analytics into ERP project management to improve success rates and enable organizations to fully leverage the benefits of ERP systems. Despite its contributions, this research has certain limitations. The dataset utilized in this research is partially synthetic. Though the foundation of the dataset is built using real project data, such as records from the "Prediction of Failures in Project Management Knowledge Areas" dataset (Taye & Feleke, 2022), the insufficient number of open-access ERP-specific project failure records necessitated adding synthetically generated entries to the dataset. These synthesised accounts were added up to stand for ERP-specific failure factors from the literature, such as technical complexity, organisational resistance, and management of resources. Statistical realism was preserved with caution, but synthesised data by definition will be less surprising and complex than real cases. In future work, greater proprietary ERP implementation data availability from organizations would enhance model precision and contextual accuracy. Collaborating with ERP vendors or consulting allies may enable the collection of high-fidelity datasets that more accurately reflect the nuance of these types of projects. Additionally, the ability to have a greater feature set to include qualitative measures such as levels of stakeholder engagement, change management effectiveness, and post-implementation support quality would provide a holistic view of ERP success and failure.

REFERENCES

[1]. Allam, H., & Akre, V. (2021, March 17). A proposed model for IT project success factors. 2021 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE). 2021 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE), Dubai, United Arab Emirates. https://doi.org/10.1109/iccike51210.2021.9410710

[2]. Chen, C. C., Law, C., & Yang, S. C. (2009). Managing ERP implementation failure: A project management perspective. IEEE Transactions on Engineering Management, 56(1), 157–170.

[3]. Garg, P., & Garg, A. (2013). An empirical study on critical failure factors for enterprise resource planning implementation in the Indian retail sector. Business Process Management Journal, 19(3), 496–514.

[4]. Griffith, A. F., Gibson, G. E., Hamilton, M. R., Tortora, A. L., & Wilson, C. T. (1999). Project success index for capital facility construction projects. Journal of Performance of Constructed Facilities, 13(1), 39–45.

[5]. Ibraigheeth, M. A., & Fadzli, S. A. (2020, October 13). Software project failures prediction using logistic regression modeling. 2020 2nd International Conference on Computer and Information Sciences (ICCIS). 2020 2nd International Conference on Computer and Information Sciences (ICCIS), Sakaka, Saudi Arabia. https://doi.org/10.1109/iccis49240.2020.9257648.

[6]. Kutsch, Elmar. (2007). The measurement of performance in IT projects. IJEB. 5. 415-426. 10.1504/IJEB.2007.014786.

[7]. Kwon, J.-H., & Kim, E.-J. (2020). Failure prediction model using iterative feature selection for industrial Internet of Things. Symmetry, 12(3), 454.

[8]. Serrador, P., & Turner, R. (2014). The relationship between project success and project efficiency. Project Management Journal, 46(1), 30–39.

[9]. A., A.-S., & A., A. (2018). How do we measure project success? A survey. https://www.longdom.org/open-access/how-do-we-measure-project-success-a-survey-2175-7866-1000229.pdf

[10]. Taye, G. D., & Feleke, Y. A. (2022). Prediction of failures in the project management knowledge areas using a machine learning approach for software companies. SN Applied Sciences, 4(6). https://doi.org/10.1007/s42452-022-05051-7

[11]. The Costly Mistake of Skipping Project Management in ERP Implementations. (2024b, June 26). 365 Digital Technologies. https://365digitaltech.com/the-costly-mistake-of-skipping-project-management-in-erp-implementations/

[12]. Thomas, M., Jacques, P. H., Adams, J. R., & Kihneman-Wooten, J. (2008). Developing an effective project: Planning and team building combined. Project Management Journal, 39(4), 105–113.