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Predictive Analytics for Project Risk Management Using Machine Learning

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Abstract

Risk management is relevant for every project that which seeks to avoid and suppress unanticipated costs, basically calling for pre-emptive action. The current work proposes a new approach for handling risks based on predictive analytics and machine learning (ML) that can work in real-time to help avoid risks and increase project adaptability. The main research aim of the study is to ascertain risk presence in projects by using historical data from previous projects, focusing on important aspects such as time, task time, resources and project results. t-SNE technique applies feature engineering in the reduction of the dimensionality while preserving important structural properties. This process is analysed using measures including recall, F1-score, accuracy and precision measurements. The results demonstrate that the Gradient Boosting Machine (GBM) achieves an impressive 85% accuracy, 82% precision, 85% recall, and 80% F1-score, surpassing previous models. Additionally, predictive analytics achieves a resource utilisation efficiency of 85%, compared to 70% for traditional allocation methods, and a project cost reduction of 10%, double the 5% achieved by traditional approaches. Furthermore, the study indicates that while GBM excels in overall accuracy, Logistic Regression (LR) offers more favourable precision-recall trade-offs, highlighting the importance of model selection in project risk management.

Keywords

Predictive Analytics, Project Risk Management, Decision-Making, Data-Driven Strategies, Risk Prediction, Machine Learning, Historical Data

1. Introduction

The current state of IT projects demonstrates that, even with the latest in technology, innovative procedures, and sophisticated systems, the success rate of IT development remains below expectations. Nevertheless, projects that fail cost billions of dollars. The success of IT projects has stagnated in 2013 [1]. Even if the success rate began to rise that year, IT initiatives are still necessary to raise the success rate. IT initiatives are risky by nature, with high stakes involved throughout the whole process. IT initiatives are fraught with a wide range of hazards, most of which have a likelihood and effect that fall between low and high [2].

The two most important things in every IT project are risk identification and management. Collaboration between predictive analytics and knowledge management would be very beneficial. Understanding the requirements, software design, human resources, technical, module integration, feasibility, and any other step in the process is fraught with potential dangers [3] [4]. The risk changes and must be closely monitored due to the fact that every project is distinct and unique. According to one source, "If senior managers fail to detect such risks, such projects may collapse completely" [5].

Numerous data points from the IT project must be analysed in order to apply IT project risk management. The report examines the project's potential outcomes [6] [7], including the causes and impacts of those outcomes, the likelihood of those outcomes occurring, and the project's influence on the business [8]. There are a lot of unknowns with the IT project, therefore, it's important to keep certain data organised and easy to find. Potential risk management tools include big data predictive analytics [9].

Several theories and methods have helped the use of predictive analytics in risk assessment; data mining extracts significant inferences from vast amounts of information. The use of data mining means analysing big data to identify patterns that help ML algorithms make future predictions [10]. The research problem addresses the persistent challenge of high failure rates in projects despite advancements in technology and management practices. Traditional risk management approaches often fall short in predicting and mitigating risks effectively. This study seeks to explore how predictive analytics and machine learning can enhance the identification and management of risks in projects by analysing historical project data, thus providing a more proactive and data-driven approach to improving project outcomes and reducing failures.

1.1. Motivation and Novelty of Study

The motivation behind this research stems from the increasing complexity of project management in modern industries, where traditional risk assessment methods struggle to handle the dynamic nature of projects and the vast amount of data generated. With increasing complexity, effective progress and timely risk responses are said to be real-time risk identification and management. This research seeks to fill these gaps by applying machine learning (ML) methods that can predict risks from past project data in order to inform decision-making. The proposed feature engineering method uses t-SNE to reduce dimensionality successfully in a pre-processing step, and a more advanced model selection besides being based on GBM, differentiating this research from previous studies which used either static or less complex models.

1.2. Contribution of Study

This research makes a great contribution to the existing body of knowledge regarding project risk management by creating an approach based on the machine learning algorithm to drive the risk prediction model in real-time mode. The key contributions are as follows:

- Data-Driven Risk Identification: Introduces a novel ML technique of risk assessment as the client's historical data about the projects are being analysed; It brings a positive change to risk management approaches and makes decisions more accurate.
- Feature Engineering through t-SNE: Illustrates an application of t-SNE (t-distributed Stochastic Neighbor Embedding) to reduce dimensionality, combat the problem of having big data, while still keeping important defining factors for the prediction model and keeping the model efficient.
- Model Selection and Performance: Focuses on the ability to predict project risk by utilising the Gradient Boosting Machine, which is more adequate than Logistic Regression and extends the body of knowledge regarding risk modelling.
- Evaluation Metrics: Sets up a general assessment model, which includes using the F1-score, precision, recall, and accuracy while evaluating the performance of risk prediction models to avoid misunderstandings in future studies.

1.3. Justification

The approach used in this work is justified by the unpredictability of interactions in projects, which could not be captured using linear techniques like PCA or LDA; Instead, t-SNE was used for feature engineering due to its ability to maintain the local architecture of the data. The detailed pre-processing of the data, such as dealing with missing values, removing outliers and scaling down the features, provides the Gradient Boosting Machine (GBM) model with clear and high-quality input. The selected performance metrics (accuracy, precision, recall, and F1-score) provide a comprehensive evaluation of the model's effectiveness in predicting project risks, directly contributing to practical project outcomes like improved risk identification, resource optimisation, and cost reduction. This integrated approach ensures the model is both robust and impactful for managing project risks in real-world applications.

1.4. Structure of Paper

The paper consists of five main parts. Section II provides the literature review on this topic. Methodology of this paper is discussed in Section III, Section IV provide the experimental results of ML models with comparative analysis, last Section V provide the conclusion of this work with future work.

2. Literature Review

A thorough literature review on risk management using various methodologies and strategies is presented in this section. Also, **Table 1** provide the summary of the related work with key area focused.

In this study, Roy (2023), a risk matrix is used to analyse a risk assessment that is based on recognised hazards. The study's findings address the difficulties and possible gains from using ML in the building sector. The research highlights the need for expertise in order to comprehend datasets that are special to a certain project. Examining issues with data consistency that impact data dependability, the research mainly focuses on unstructured text and image data. Despite the study's acknowledgement of ML's ability to digitalise and simplify construction procedures, it highlights obstacles, including data security [11].

This paper (2022) places an emphasis on predicting software project failure early on as a means of risk assessment. Various methods of ML will be used. Machine learning is used in the development of the model. LR, NB, SVM, DT neural networks, and adaptive neuro-fuzzy inference systems were chosen as six methods to diversify the model. This work advances the area of software system development by creating models for software project risk assessment that are broadly applicable to any software project at any stage of the software development lifecycle [12].

This study Elokby *et al.*, (2021) enforced project risk management procedures and made the IT project successful in Egypt's telecom and IT industries. There were four metrics used to evaluate the success of the IT projects: Project scope, project quality, project cost, and project time (schedule). Identification of risks, preparation for managing those risks, evaluation of those risks (both qualitative and quantitative), preparation for responding to those risks, actual execution of those responses, and monitoring of those results are all parts of risk management. In order to fulfil the goals of this study, a questionnaire was created as the primary means of gathering primary data [13].

This study Owolabi *et al.*, (2020) suggests a method for predicting completion risk using Big Data Analytics predictive modelling. There are linear regression, regression tree, RF, SVM, and DNNs were built and validated for a completion risk predictive model using the dataset of 4294 PPP project samples delivered across Europe between 1992 and 2015. The conclusion and result of the study prove that, with a less average test prediction error compared to other traditional regression tools, random forest could be a valuable tool in predicting delays in PPP projects. Other aspects included in this study are the questions related to the choice of model, its training and validation [14].

This paper Mahdi *et al.*, (2020) offers a review of current literature regarding the establishment of methodological innovations in the area of ML for software risk analysis. The analysis of this review has also highlighted some patterns in the methodologies of ML, size measures, and the findings that have shaped and advanced progress of ML in project management. Besides, this study provides a better understanding and a profound foundation for more research about software project risk assessment work. Additionally, it offers an additional method to minimise the likelihood of failure and improve the software development performance ratio, and it increases the likelihood that a software project will be anticipated and prepared to handle [15].

The article Burkov *et al.*, (2020) takes into account the responsibility of overseeing projects' and programs' hazards. Qualitative risk assessments are often used in practice to determine the degree of effect and the likelihood of harm. A three-point risk scale (low, medium, and high) is the most often used. The approach to managing risks in projects and programs, which relies on qualitative

Table 1. Summary of previous study on project risk management using machine learning.

Authors	Focus	Methodologies	Key Findings	Limitations	Future Work
Roy [11]	Risk assessment in construction.	Risk matrix, analysis of unstructured text and image data.	Highlights ML's role in digitalising construction, emphasises need for expertise, data security issues.	Limited generalizability due to project-specific datasets.	Explore other area for broader insights.
Unnamed Authors [12]	Predicting software project failure.	Logistic Regression (LR), Naive Bayes (NB), Support Vector Machine (SVM), Decision Trees (DT), Neural Networks, Adaptive Neuro-Fuzzy Inference Systems.	Develops a reliable risk assessment model applicable to any software project at any lifecycle stage.	Models may not account for all project variables and complexities.	Test models on diverse projects to enhance robustness and adaptability.
Elokby *et al.* [13]	IT project success in telecom and IT industries.	Risk management procedures, qualitative and quantitative evaluations.	Successful project metrics identified; emphasizes comprehensive risk management practices.	Limited to the telecom and IT sectors; results may not be generalised.	Expand the study to include other industries and sectors.
Owolabi *et al.* [14]	Predicting completion risk using Big Data.	Linear Regression, Regression Tree, Random Forest (RF), SVM, Deep Neural Networks (DNNs).	Random Forest found effective in predicting delays in PPP projects with lower average prediction error.	Dependence on historical data may not capture future project dynamics.	Incorporate real-time data and feedback loops for adaptive modelling.
Mahdi *et al.* [15]	Literature review on ML in software risk analysis.	Methodological innovations in ML, literature analysis.	Identifies patterns in ML methodologies; provides foundation for future research in software project risk assessment.	The review scope may overlook recent developments in ML techniques.	Update the review periodically to include emerging methodologies.
Burkov *et al.* [16]	Qualitative risk assessment in projects.	Qualitative risk assessments, three-point risk scale.	Critiques reliance on qualitative evaluations suggest the need for improved risk management strategies.	The subjective nature of qualitative assessments may lead to bias.	Develop quantitative framework to complement assessments.

evaluations and employs methods to avoid or reduce risks, have not evolved enough, in our opinion. This article provides an overview of risk aversion and risk reduction, several ways to accomplish these objectives, and a method for determining the qualitative features of potential dangers [16].

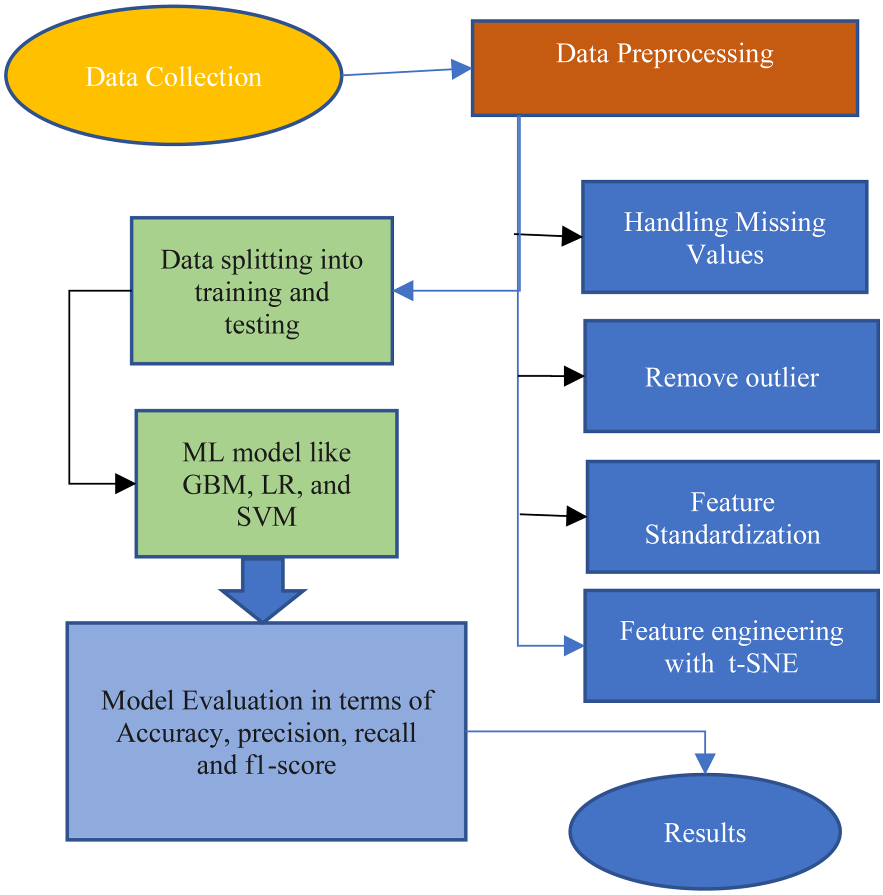

Figure 1. Flowchart for project Risk management.

As shown in **Figure 1**, there are different phases of the project risk management and all the stages are clearly explained below.

3. Methods and Materials

The methodology for Predictive Analytics for Project Risk Management Using ML begins with collecting historical project data, including timelines, task durations, resource allocations, and project outcomes, to capture key factors influencing project success. Following this, data preprocessing is conducted to handle missing values, remove outliers, and standardise features, ensuring data quality and consistency for modelling. Feature engineering is performed using t-SNE to reduce dimensionality while preserving data structure. Consequently, the data is partitioned into a training section (70%) and a test section (30%) for evaluation purposes. Gradient Boosting Machine or GBM is used as the primary classification algorithm to predict project risks based on the least loss function by iteratively boosting the selected model. Algorithms including accuracy, precision, recall, and F1-score are used to assess the forecasts' accuracy and how best to use them to guide risk management decision-making.

3.1. Data Collection

A process starts with a large-scale data gathering campaign, with data on as broad a set of project history as possible. The collected data extends but is not limited to the following, project schedules, separate task schedules, and resources assigned to each task and project, and the results of these projects. This kind of collection of data is important since most of the aspects of project management are complex and may involve different factors that might affect a success of a project.

3.2. Data Preprocessing

Data preprocessing meaning pertains to the processes that are taken through to clean data and make them fit for other uses. However, before using it in machine learning algorithms, a set of operations has to be performed in order to enhance its quality. Data normalisation, consistency checking, and managing missing values are essential parts of data preparation. Here are the main pre-processing techniques:

- **Handling Missing Values:** The ways to deal with measurements with missing values include methods where missing values will be filled in based on median or mode of the data.
- **Remove Outliers:** The identification and other portions are ideal while conducting data preprocessing in machine learning to avoid biases. For the data efficiency, the next step is to delete the outlier from the dataset.

3.3. Feature Standardization

In cases where numerical inputs are used in feeding data, a feature standardisation process is conducted so that all inputs are normalised. This means that elements with large relative sizes cannot dominate the learning process which is very important for models that depend on the scale of the characteristics. To standardize a numerical attribute aj Compute the standardized value a_{ij}^{*} as follows (1):

$$a_{ij}^{*} = \frac{a_{ij} - \mu_{aj}}{\sigma_{aj}} \tag{1}$$

where μ_{aj} is a mean and σ_{aj} is a standard deviation of attribute aj across all projects.

3.4. Feature Engineering with t-SNE

The use of feature engineering with t-Distributed Stochastic Neighbour Embedding (t-SNE) was utilised to decrease a data dimentionality in order to retain its essential structure. This made it easy to determine features that are important to projects and whose absence would greatly affect project results, helping build better predictive models.

t-Distributed Stochastic Neighbor Embedding (t-SNE) was chosen over alternatives like Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) for its ability to handle non-linear relationships between features while preserving the local structure of the data. This is crucial in project management data where task dependencies, resource allocation, and project outcomes often follow non-linear patterns.

3.5. Data Portioning

As part of the experimental setting, the dataset was divided into two parts: The training set, which included 70% of the data used to train the models, and the testing set, which had 30% of the data.

3.6. Classification with Gradient Boosting Machine (GBM)

Belonging to the family of ensemble learning methods, the GBC is an effective ML approach. By integrating boosting and gradient descent, it generates a trustworthy prediction model. One common approach to iterative optimisation is to use DT to create a set of fundamental forecasting models, which are then fed into GBC [17]. It is possible to modify the learner models and the loss function simultaneously. In order to minimize the loss function, gradient boosting is applied to certain data samples. This method uses gradient descent to reduce the loss to a minimum. Equation (2) shows that the technique minimise the loss function.

$$\hat{F}(x_i) - \min_{f(x_i)} \sum_{i=1}^{n} \mathcal{L}(y_i, F(x_i)) \tag{2}$$

The observed value is denoted as y_i, and the model formed by merging the weak learners is denoted as $\hat{F}(x_i)$ [18].

3.7. Performance Measures

A performance matrix comparing real observations with model predictions was used to assess an effectiveness of a chosen models. Some of the criteria included in the performance matrix were Recall, F1-score, precision, and accuracy. A following metrics were computed for various classes: A higher number of True Positives (TPs) indicates that positive cases were properly identified, while a lower number indicates that True Negatives (TNs) were correctly classified negative occurrences. those that are mistakenly classified as positive are known as False Positives (FPs), while those that are improperly classified as negative are known as False Negatives (FNs). The chosen performance metrics—accuracy, precision, recall, and F1-score—are all directly related to practical outcomes in project risk management.

The following formulae may be used to represent the assessment metrics:

Accuracy: An 85% accuracy indicates that the model correctly identifies project risks in the majority of cases, which provides project managers with reliable information on potential risks. It enhances decision-making and reduces the chances of having to address emerging issues temporally. The formula (3):

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{3}$$

Precision: Precision of 82% suggests that when the model predicts a project risk, it is mostly correct. The following formula of precision (4):

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{4}$$

Recall: Recall of 85% shows the model's ability to identify actual project risks among all risks. In combination, they fine-tune the accurate identification of potential risks with low numbers of false positive findings. The formulation of recall is (5):

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5}$$

F1-score: Thus, it shows the balance between the risk identification and avoiding false positive/negative values of 80% by the F1-score, which is the harmonic mean of precision and recall. This balance is crucial for project managers as they need accurate predictions that lead to effective intervention without overburdening resources. The F1-score formula is (6):

$$\text{F1-Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6}$$

As a means of aiding decision-making and providing an objective measure of the models' performance, this study used these four measures to assess the ML models.

4. Result Analysis and Discussion

The experimental study was designed to validate the effectiveness of integrating predictive analytics into project management processes, focusing on outcome prediction and resource optimization. By leveraging a dataset comprising historical project data, the study aimed to demonstrate how predictive analytics could enhance project managers' ability to forecast project outcomes accurately and allocate resources more efficiently. The following Table 2 provides the performance of GBM model across performance matrix.

Table 2. Historical project data based GBM model performance.

Measures	Gradient boosting machine
Accuracy	85
Precision	82
Recall	85
F1-Score	80

An impressive 85% accuracy, 82% precision, and 85% recall were attained by the GBM model, as shown in Table 2 and Figure 2, indicating outstanding classification performance. Precision and recall are both well-balanced with an F1-Score of 80%.

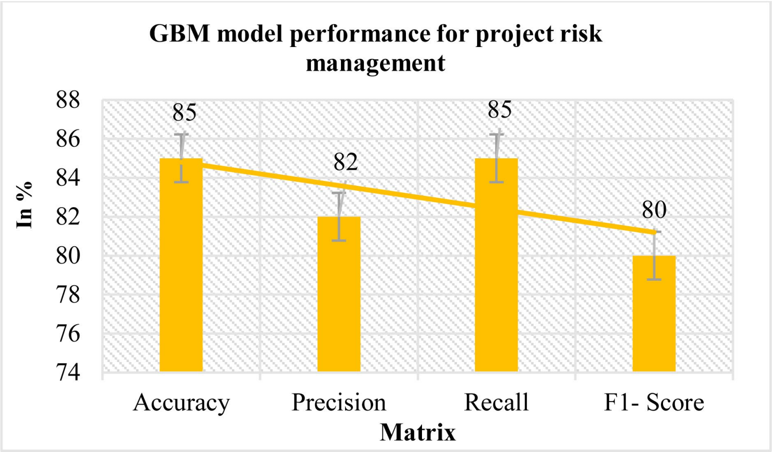

Figure 2. GBM model performance.

Figure 3. Line graph for model performance over iterations.

A line graph as shown in Figure 3 illustrates the improvement in model accuracy over different iterations of hyperparameter tuning. An x-axis displayed a total number of iterations, while a y-axis displays a percentage of correctness. A graph displays a clear upward trend, indicating that model performance improves as the tuning process progresses. This indicates that the model is capable of refining its predictions and adjusting to different types of projects.

The bar graph Resource Optimisation Efficiency and Project Cost Reduction in Figure 4 illustrates that Predictive Analytics significantly outperforms Traditional Allocation in both metrics. Predictive Analytics achieves 85% in Resource Utilization Efficiency compared to 70% for Traditional Allocation, and 10% in Project Cost Reduction, double the 5% achieved by Traditional Allocation. This demonstrates the superior effectiveness of Predictive Analytics in optimizing resources and reducing project costs. Resource management improves concurrently with the outcome of projects since efficiency in the usage of available resources enhances the completion of projects promptly and cost-effectively.

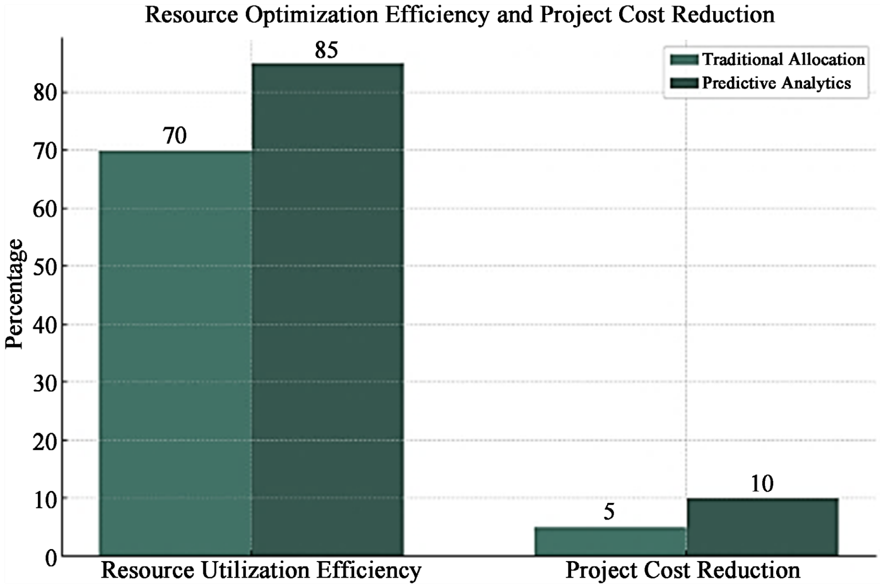

Figure 4. Resource optimization efficiency.

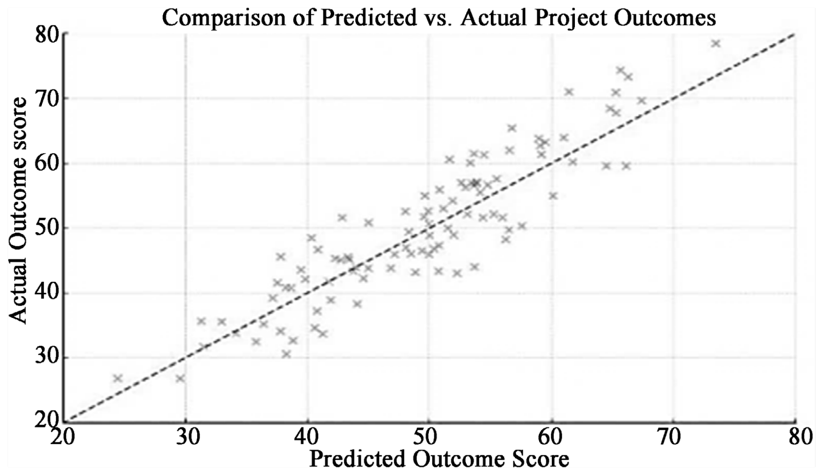

Figure 5. Comparison of predicted vs. actual project outcomes.

Figure 5, which compares projected and actual project outcomes, displays a scatter plot that demonstrates that, for most projects, the predictions and actual results are in agreement. Each green "x" represents a data point comparing a predicted score to an actual score. The red dashes on the figure line depict the state of precise predictive accuracy when the forecasted score is the same as the actual score. This supports the notion that the model can effectively predict risks and returns within projects in order to assist project managers. The proximity of the predicted values to the actual observation further corroborates the validity of applying ML in risk assessment of projects.

4.1. Discussion

The experimental findings reveal the great benefits of adopting the use of predictive analytics in project management. A significantly higher level of classification accuracy is shown by the Gradient Boosting Machine (GBM) model, with the accuracy estimated at 85%, precision at 82%, and recall at 85%, which proves the high efficiency of this model for further accurate prediction of project outcomes. The gradual increase in value of model accuracy as displayed above shows that the model can be tweaked in future hyperparameter tuning iterations with resultant better performance metrics. Additionally, predictive analytics achieves a resource utilisation efficiency of 85%, compared to 70% for traditional allocation methods, and a project cost reduction of 10%, double the 5% achieved by traditional approaches. The real-world data presenting the outcomes of the projects as plotted in the scatter plot of the predicted against actual results has shown a lot of congruity of the results of the predictive model. Overall, these findings are closely associated with the notion of how big data can change the nature of concurrent decision-making and improve the existing approaches to project management.

4.2. Comparative Study

This section provides a comparative analysis between ML models for project risk management. The ML models are GBM, LR [12], and SVM [12] that compare across performance parameters.

Figure 6 shows a comparison of model performance. The GBM achieved

Table 3. ML model comparison on historical dataset.

Model	Accuracy	Precision	Recall	F1-Score
GBM	85	82	85	80
LR	71	83	77	87
SVM	83	84	77	83

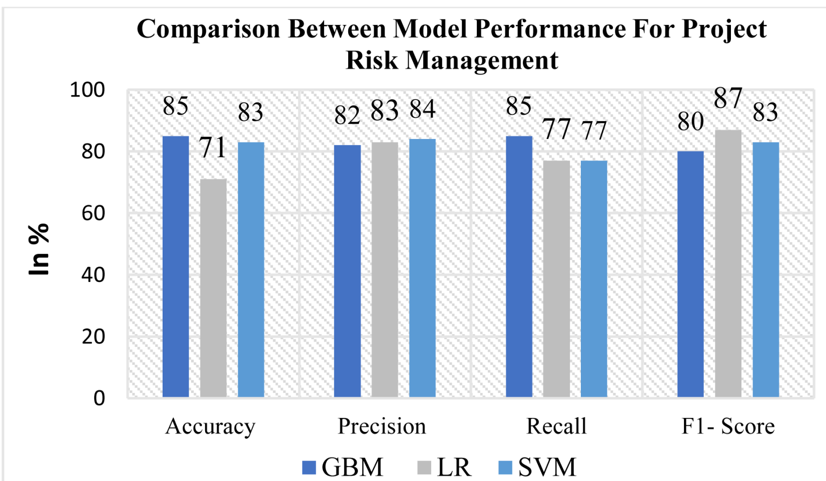

Figure 6. Comparison between model performance.

the highest accuracy at 85%, with a precision82%, a recall 85%, and an F1-score 80%. On the other hand, the LR model reported fewer accuracy at 71%, but it had the best precision at 83% and F1-score at 87% to guarantee the method's FP and FN. The SVM, provided a good performance with an accuracy 83%, precision84%, recall 77% and an F1 measure 83%. These findings imply that even though GBM is most accurate, LR provides better trade-off among precision and recall and is, therefore, more suitable in conditions where true positives are significant.

5. Conclusion and Future Scope

Risk assessment is an important part of every management process, especially for large and long-life projects and projects that exist in a state of constant change. Conventional risk management tools are mostly inadequate for such environments, perhaps explaining why a more reliable means of risk assessment is required. This study suggests the use of an (LR) and a (GBM) as ML tools to improve the risk prediction model. The characteristics, scale, cost, amount of effort and duration of project, etc., which are identified to influence the likelihood and prevalence of risks, indicated that the proposed models have a strong potential to act as risk predictors. These findings stated that GBM was more responsive with an accuracy of 85%, precision of 82%, recall of 85%, and F1-score of 80%, and thus, it can be considered a very effective tool in project risk management. Still, precision-recall trade-off was more favorable for LR, whereas this could be preferable in tasks, where both are essential.

However, the study has limitations, though the obtained results demonstrate optimism. The sources of data used in this research may not contain all the aspects of project risk because most of them revolved around time, task length, resources and results. Future studies should envisage considering more risk-related variables and the assessment of different ML methods' effectiveness. Also, the further investigation of more elaborate feature selection approaches may be beneficial for enhancing the results of a project risk-related analysis by providing for more subtle characteristics captured in the data. More data and better model calibration could enable more dependable and universally applicable findings for improving on predictive analysis for risk in projects.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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