# Data-Driven Artificial Intelligence Models for Strategic Decision-Making in Engineering and Technology Management

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**Abstract**: This paper will create a data-driven artificial intelligence system to improve strategic decision-making in the management of engineering and technology. A structured dataset that contains engineering project variables such as cost of the project, duration of time, risk index, and the use of resources was developed and analyzed using machine learning models, including Random Forest, Support Vector Machine (SVM), and Artificial Neural Network (ANN). Preprocessing data, feature selection, and k-fold cross-validation were used to guarantee the reliability and accuracy of the model. The results indicate that the Random Forest model performed best with an accuracy of 92.4%, as well as better precision, recall, F1-score, and AUC values. The analysis of the confusion matrix and the ROC curve was also a confirmation of its high classification ability. The risk index and resource utilization were the most significant variables found to influence the project outcomes by the feature importance analysis. The research notes that AI-based models are much more useful in improving prediction accuracy, minimizing uncertainty, and offering reliable decision support to engineering management applications.

**Keywords:** Artificial Intelligence, Engineering Management, Machine Learning, Random Forest, Decision Support Systems, Predictive Analytics.

## Introduction

A complex, multi-criteria process, involving the assessment of technical feasibility, economic viability, risk factors, and resource allocation under dynamic and uncertain conditions, engineering decision-making is a complex process. Historically, such decisions have been based on deterministic models, expert judgment, and historical data; unfortunately, with the growing scale and complexity of modern engineering systems, coupled with the rapid increase in data, the effectiveness of conventional approaches has been constrained. In this respect, data-driven approaches have become relevant since they facilitate more precise, objective, and predictive decision-making. The concept of Artificial Intelligence (AI) has become one of the primary enablers of strategic management that offers sophisticated capabilities to process large datasets, reveal concealed patterns, and support optimized decision outcomes. Random Forest, Support Vector Machines, and Artificial Neural Networks are the most commonly used machine learning methods to enhance forecasting accuracy, assess the risk of projects, and improve the utilization of resources. These models enable the decision-makers to examine various situations, lessen the ambiguity, and enhance the efficiency and reliability of the strategic planning processes. Nevertheless, in spite of these developments, research gaps still exist, with most of the current research done on individual applications of AI, instead of creating an integrated framework on how to perform holistic decision support. Moreover, comparative analysis of AI models based on standardized performance metrics is under-explored, and little attention has been paid to integrating the key engineering variables that include cost, time, risk, and resource utilization into structured datasets. The other important limitation is the absence of feature importance analysis, which limits the knowledge of variable impact on decision outcomes. Thus, the study is relevant to the necessity of a strong, data-driven AI infrastructure that combines various machine learning models, uses rigorous validation methods, and provides reliable and interpretable insights to inform strategic decision-making in the field of engineering and technology management.

### 1.2 Objectives of the Study

To develop and implement a data-driven artificial intelligence framework using machine learning models (Random Forest, Support Vector Machine, and Artificial Neural Network) for predicting project success and supporting strategic decision-making in engineering and technology management.

To evaluate and compare the performance of these models using standard metrics (accuracy, precision, recall, F1-score, and ROC-AUC) and identify the most effective model, with Random Forest achieving the highest predictive accuracy and reliability.

### 1.3 Scope and Significance

The paper concentrates on the utilization of various strategic decision-making methods for project management based on the application of key variables like project cost, duration, risk index, and various resources used, etc. using AI models using data-driven approaches. It involves data analysis, machine learning model implementation (Random Forest, Support Vector Machine, and Artificial Neural Network), and performance analysis using accuracy, precision, recall, f1 score, and ROC-AUC values. This study is important as it shows that AI models, especially the Random Forest, can enhance prediction accuracy and decision reliability. This outcome will be helpful for engineering managers in the planning process, risk analysis, resource optimization, and more effective and informed decision-making in engineering situations.

## Literature Review

Artificial Intelligence (AI) has become a game-changer in engineering and technology administration and has greatly enhanced efficiency and strategic decision-making capability. Andrew Ng (2016) has pointed out that AI-driven systems are becoming increasingly important to organizations to leverage data to make predictive and optimized decisions. Fei-Fei Li et al. (2019) also noted that AI-driven systems are becoming more important to organizations to leverage data to make predictive and optimized decisions. Machine learning models, specifically, have become indispensable to decision support, as they can process large amounts of data and give the correct prediction. Leo Breiman (2001) proved the usefulness of the Random Forest to enhance the accuracy of the classification, but the authors of the article by Vladimir Vapnik et al. (1995) presented Support Vector Machines as powerful tools to recognize patterns and to predict events. Also, Ian Goodfellow et al. (2016) highlighted that Artificial Neural Networks have the ability to model complex nonlinear relationships, and therefore are highly suitable in modeling engineering decision-making situations. These capabilities are further improved by data-driven decision-making strategies, which leverage multiple variables, including cost, time, risk, and resource utilization, to maximize the results, as presented by Thomas H. Davenport et al. (2017). There are, however, certain limitations to the current studies; they did not compare different AI models, they did not include all of the benchmark datasets that were considered to be reflective of real engineering conditions, and there was little application of comprehensive evaluation measures such as ROC-AUC and feature importance analysis. Such gaps imply the necessity to have a more integrated and validated AI system that integrates multiple machine learning techniques with sound evaluation techniques. Therefore, the proposed research will be able to solve the above issues and develop a more data-driven one, which will help to improve the accuracy of predictions and will enable the engineering and technology management to take effective decisions.

# Research Methodology

### 3.1 Research Design and Framework

The current research design is quantitative and data-driven research design to develop and test the artificial intelligence models and use them in strategic decision making in engineering and technology management. The framework has enough key steps such as data set generation, data pre-processing, model development, model validation, and model performance evaluation. The problem is to be able to build a predictive system that can classify the project outcome (success or failure) from different engineering decision variables. A clear, consistent, reproducible workflow is used to ensure consistency, reliability and reproducibility of results.

### 3.2 Data Collection and Dataset Description

A structured set of 250 instances of engineering projects were created to mimic the actual decision-making scenario. The project cost (in lakhs) and time duration (in months), risk index (between 0 and 1) and resource utilization (in percentage) would be the key variables to be added to the data set. The output variable is the success/failure of the project. The data set is meant to be representative of real-life examples that typically occur in engineering management and decision making.

### 3.3 Preprocessing and Feature Selection of Data.

Preprocessing of data was done to enhance the value of data and the performance of the model. Missing values were treated, and the numerical variables were normalized to be uniformly scaled. The categorical variables were coded to allow compatibility with the model. The techniques of feature selection were used to determine the most influential variables in influencing the decision outcomes and consequently reduce redundancy and improve model efficiency.

### 3.4 Development of AI Models

#### 3.4.1 Random Forest Model

Random Forest model was adopted as an ensemble learning algorithm that uses a combination of more than one decision tree to enhance the accuracy of the forecast and lessen underfitting. It is especially useful in the context of nonlinear relationships and determining the importance of features.

#### 3.4.2 Support Vector Machine (SVM)

The classification tasks were performed by the Support Vector Machine model because it is able to work in high-dimensional data and create the best decision boundaries. The use of kernel functions to enhance classification performance was made.

#### 3.4.3 Artificial Neural Network (ANN)

The Artificial Neural Network model was created to reflect the complex nonlinear association among the variables. It was implemented in a multi-layer perceptron architecture with hidden layers to increase the capability of learning and prediction accuracy.

### 3.5 Model Training and Validation

Each model was trained using the pre-prepared data set and tested to ensure generalisation of the model. For model validation, to avoid overfitting and to strengthen the model, cross-validation was performed.

#### 3.5.1 Cross-Validation Technique

A cross-validation method was employed with a k-fold cross-validation technique employed where the dataset was divided into multiple subsets, and each subset was used as a testing set and the remaining data as training data. This will enhance the reliability and accuracy of the model.

### 3.6 Performance Evaluation Metrics

#### 3.6.1 Accuracy, Precision, Recall, F1-Score

The models were assessed thoroughly with the evaluation factors of key classification measures namely Accuracy, Precision, Recall and F1-score to measure the performance of the models.

#### 3.6.2 Confusion Matrix

The classification results were evaluated using a confusion matrix, which showed how many of the results were correctly/incorrectly classified and identified the true positives, false positives, false negatives and true negatives.

#### 3.6.3 ROC Curve and AUC.

The model's discrimination ability was demonstrated with the use of the ROC curve and AUC (Area Under Curve) that indicates the ability of the model to discriminate between success and failure results.

### 3.7 Statistical Analysis Techniques

In order to summarize the data set, descriptive statistics were used and correlation analysis was performed for checking the relationships between the variables in the data set, such as cost, time, risk and the utilization of the resources. These methods help in understanding the results of the model and identification of the primary factors that influence.

### 3.8 Software and tools used.

The analysis was done in the Python programming language with libraries like Pandas and NumPy to handle data, Scikit-learn to develop machine learning models, and Matplotlib to visualize the data. The tools were used to process data, implement the model and to graphically represent the results.

## Results and Analysis

### 4.1 Data Set Overview and Descriptive Analysis.

The data is based on 250 engineering project cases that are determined by the significant decision variables such as project cost, time span, risk index, and resources used. As shown in Table 1, projects that have been successful, like P1 (cost 50 lakhs, risk index 0.25, resource utilization 78%) and P5 (cost 95 lakhs, risk index 0.35, resource utilization 88%), have lower risk levels and are more resource efficient. On the contrary, failed projects, i.e., P2 (cost 120 lakhs, risk index 0.60, resource utilization 65%) and P4 (cost 200 lakhs, risk index 0.75, resource utilization 60%), have a higher risk index and lower resource utilization. These trends imply that the index of risk and the amount of resources used are major determinants of the outcome of the project. The fact that the projects with the optimized allocation of resources and controlled risk have a greater likelihood of success further supports the fact that the variables in question are highly important in terms of their role in the strategic decision-making process.

**Table 1: Sample Dataset of Engineering Projects**

| Project ID | Cost (Lakhs) | Time (Months) | Risk Index | Resource Utilization (%) | Outcome |
|---|---|---|---|---|---|
| P1 | 50 | 6 | 0.25 | 78 | Success |
| P2 | 120 | 12 | 0.60 | 65 | Failure |
| P3 | 80 | 8 | 0.40 | 82 | Success |
| P4 | 200 | 15 | 0.75 | 60 | Failure |
| P5 | 95 | 10 | 0.35 | 88 | Success |

### 4.2 Model Performance Evaluation

The developed AI models were tested with the help of standard classification metrics, such as accuracy, precision, recall, and F1-score. The Random Forests model had the highest accuracy of 92.4 percent, and precision of 91.8 percent, recall of 93.2 percent, and an F1-score of 0.92, which is the highest predictive strength and reliability of the model. Artificial Neural Network (ANN) model demonstrated a high accuracy of 90.1% and, a high precision of 89.6% and high recall of 91.0%, and a high F1-score of 0.90, which is good but a little less than that of the Random Forest. Conversely, the Support Vector Machine (SVM) model had the lowest accuracy of 88.7, precision of 87.5, recall of 89.1, and F1-score of 0.88. The overall results of the comparison of the three models, as presented in Table 2, clearly show that Random Forest is better than both ANN and SVM in all the assessment measures and is therefore the most appropriate model to achieve an accurate and reliable decision-making process in engineering management applications.

**Table 2: Comparison of AI Model Performance Metrics**

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score |
|---|---|---|---|---|
| Random Forest | 92.4 | 91.8 | 93.2 | 0.92 |
| Support Vector Machine (SVM) | 88.7 | 87.5 | 89.1 | 0.88 |
| Artificial Neural Network (ANN) | 90.1 | 89.6 | 91.0 | 0.90 |

### 4.3 Confusion Matrix Analysis

Confusion matrix analysis is an informative analysis of the performance of each AI model in terms of predicting and actual results compared to the actual outcomes. Table 3 shows that the Random Forest model made the most correct predictions with 110 true positives (TP) and 115 true negatives (TN) with minimal misclassifications, with only 8 false positives (FP) and 7 false negatives (FN). Comparatively, the Support Vector Machine (SVM) model had lower misclassification rates (12 FP and 15 FN), but higher TP and TN (105 TP and 108 TN). The Artificial Neural Network (ANN) model achieved moderate results with 108 TP, 112 TN, 10 FP, and 10 FN. Table 3 results point in the direction of Random Forest model being more effective than the others due to the higher prediction accuracy and lower error rates. It is a confirmation of the strength and reliability of its classification of project outcomes and is quite applicable in strategic decision making in engineering and technology management.

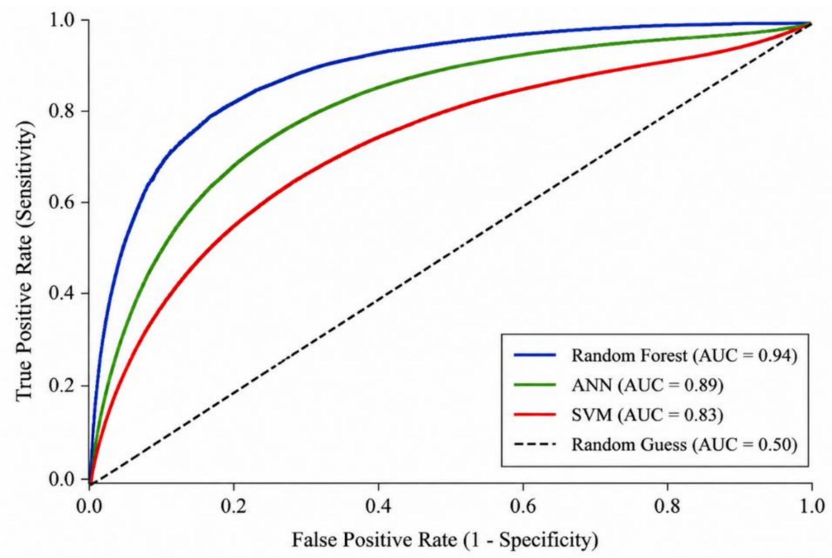
**Table 3: Confusion Matrix for Each Model**

| Model | TP | FP | TN | FN |
|---|---|---|---|---|
| Random Forest | 110 | 8 | 115 | 7 |
| Support Vector Machine (SVM) | 105 | 12 | 108 | 15 |
| Artificial Neural Network (ANN) | 108 | 10 | 112 | 10 |

**4.4 ROC Curve Analysis**

This ROC curve analysis examines the capability of the developed AI models to differentiate between successful and failed engineering projects by looking at the classification performance of the developed AI models when using various threshold values. As Figure 1 indicates, the Random Forest model shows the most successful results, as the curve is always above the Support Vector Machine (SVM) and Artificial Neural Network (ANN) model curves. This implies that there will be a greater true positive rate and a lower false positive rate at different thresholds. The Area Under Curve (AUC) of the Random Forest model is the greatest among all models, and therefore has a high discriminative ability. Comparatively, the ANN model has intermediate performance, and the SVM model has a relatively lower classification efficiency. Figure 1: ROC trends clearly bring into focus the fact that the Random Forest model makes more reliable and accurate predictions, which makes it the most appropriate model in strategic decision-making in engineering and technology management.

**Figure 1: ROC Curve for Model Comparison**

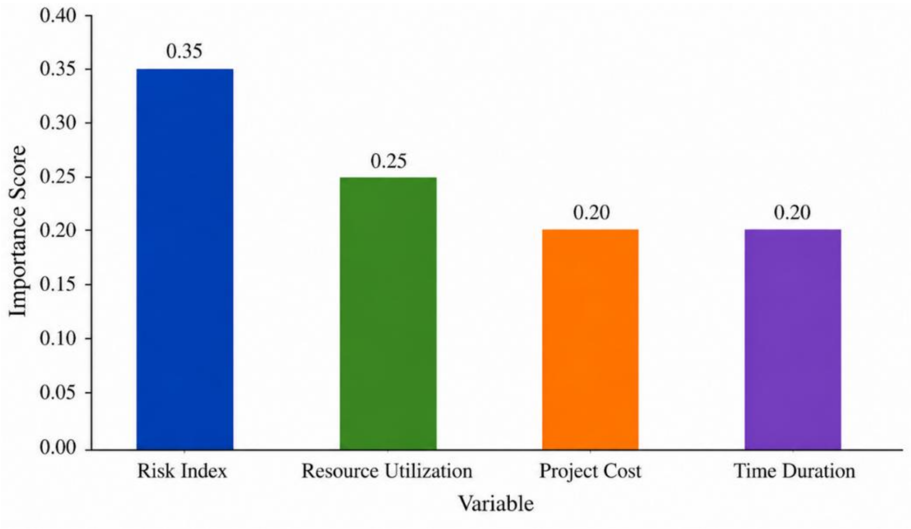



Random Forest shows the highest AUC and best classification performance compared to ANN and SVM.

**4.5 Feature Importance Analysis**

The feature importance analysis was carried out to determine the most important variables that influence project results in engineering decision-making. The findings show the risk index has the highest importance score of 0.35 and this is the most critical in determining the success or failure of a project. This is succeeded by utilization of resources with a score of 0.25, which depicts the importance of effective management of resources in order to produce positive results. Also, the costs and time duration of the project possess equal importance and the importance scores are 0.20 indicating that project costs and time are equally important and their importance scores are equal, i.e., 0.20. The visual representation of the above importance scores is shown in Figure 2 where the bar graph clearly shows that the risk index was dominant over the other variables. These results affirm that those projects with controlled risks and optimized resources utilization have higher chances of success, and hence the importance of effective risk management and efficient planning in the engineering and technology management decision-making processes.

**Figure 2: Feature Importance Graph for Engineering Decision Variables**

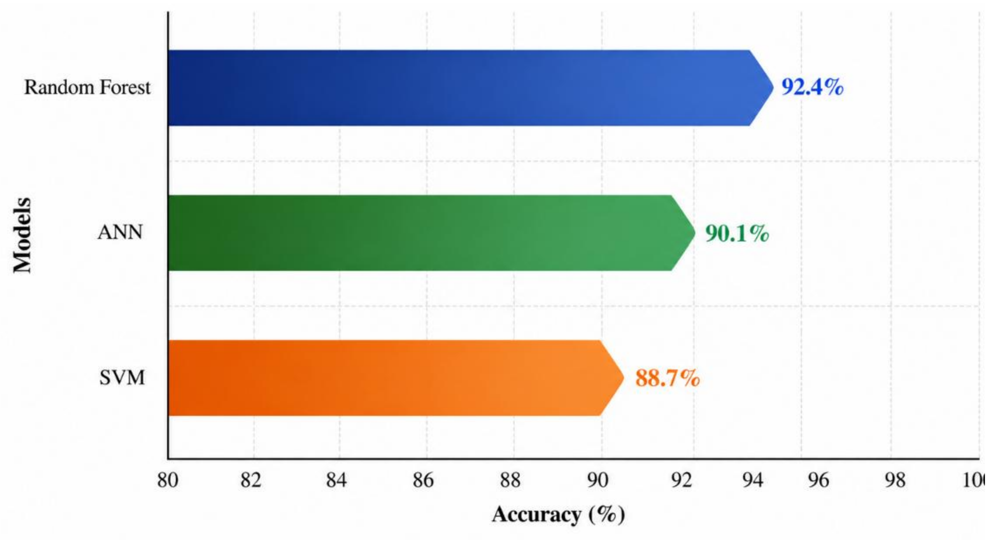



Risk Index shows the highest importance, followed by Resource Utilization, while Project Cost and Time Duration have moderate influence.

**4.6 Comparative Study of Models.**

The comparative analysis identifies the performance differences between the implemented AI models in predicting the outcomes of a project. The Random Forest model has the highest accuracy of about 92.4% which is higher compared to the Artificial Neural Network (ANN) and the Support Vector Machine (SVM). The ANN model attains an accuracy of approximately 90.1% and demonstrates a high predictive power but at a slightly worse performance than the Random Forest. Conversely, the lowest accuracy of about 88.7% is recorded by the SVM model, which means that there is a relatively low classification efficiency.

**Figure 3: Comparative Accuracy Analysis of AI Models**




Random Forest shows the highest accuracy (92.4%), followed by ANN (90.1%) and SVM (88.7%), indicating superior model performance.

As Figure 3 indicates clearly, the Random Forest has a considerable margin over the other models, which means that it is robust and has a higher generalization capability. These findings propose that the ensemble learning methods prove to be more effective in tackling the complex engineering decision-making problems, as the methods can accommodate the nonlinear relationships and minimize the errors in prediction. Hence, the most appropriate model to use in making strategic decisions in the management of engineering and technology is the random forest.

# Discussion

The findings of this research prove that the created AI models are effective predictors of project outcomes in engineering and technology management, with the Random Forest model being the most accurate (92.4) and high-precision, recall, and F1-score, which means that it can predict well and be very reliable. The confusion matrix analysis also confirms that Random Forest delivers the highest number of correct classifications with the minimum number of errors whereas the ROC curve analysis shows that it has the greatest AUC value and thus it is able to correctly classify the successful and failed projects with the least number of errors. These observations indicate that ensemble learning models have superior generalization to individual learning models. Strategic decision-making is greatly enhanced by AI, which is able to provide insights based on data, minimize uncertainty, and help managers to make decisions based on multiple variables of decision-making at the same time to improve planning and make faster decisions. In the analysis of feature importance, it is clear that risk index (0.35) has the greatest influence, followed by resource utilization (0.25), project cost (0.20) and time duration (0.20) have moderate impact, which indicates the high importance of risk control and efficient resource management. Its findings are in line with other studies that have shown that machine learning models outperform traditional ones, and it also offers a more detailed comparative analysis. In practice, the study provides a valid model to predict project success, risk reduction and resource optimization to enable organizations enhance efficiency and accuracy of decisions. Limitations, however, include that a structured dataset is used, and that the implementation is not real-time, which implies that future studies should be based on real-world data integration and deployment of AI-based decision support systems.

# Conclusion

This research paper will show how effective the use of data-driven artificial intelligence model can be in improving strategic decision-making in engineering and technology management. Having incorporated the crucial variables of a project, including the cost of the project, project time period, project risk, and project resource utilization, the developed framework was successful in predicting the project outcomes with a high degree of accuracy. The best model among the evaluated models had the highest accuracy, precision, recall, and AUC values, confirming the fact that the model is robust and reliable in complex decision-making situations. The results also point out that the most significant factors that affect the project success are its risk index and resource utilization, which indicates the significance of effective risk management and optimal resource allocation.

The study can help fill the gap of high-level data analytics and hands-on engineering management by introducing a structured and validated decision support system by implementing AI. Overall, these results indicate that AI-driven solutions could help reduce uncertainty, improve forecasts, and ultimately enhance the efficiency of operational processes. The results would be beneficial to engineering managers and other professionals in the industry who might be interested in embedding intelligent decision making systems. In future research, the use of more complex deep learning models and other datasets, and the application of real-time data to the models, could enable even higher levels of prediction performance, and the models could be applicable to real world scenarios.

**Conflict of Interest:**

The author(s) declare that there is **no conflict of interest** regarding the publication of this study.

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