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Article

Exploring the role of machine learning models in risk assessment models for developed organizations' management decision policies

Boumedyen Shannaq[1], Devarajanayaka Kalenahalli Muniyanayaka[1], Oualid Ali[2,*], Basel Bani-Ismail[3], Said Al Maqbali[1]

[1] University of Buraimi, Al Buraimi, Sultanate of Oman
[2] Computer Sciences Department, College of Arts & Science, Applied Science University, Manama, Kingdom of Bahrain
[3] Faculty of Information Technology, Majan University College, Sultanate of Oman
*** Corresponding author:** Oualid Ali, oualid.ali@asu.edu.bh

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Abstract: The goal of this work was to create and assess machine-learning models for estimating the risk of budget overruns in developed projects. Finding the best model for risk forecasting required evaluating the performance of several models. Using a dataset of 177 projects took into account variables like environmental risks employee skill level safety incidents and project complexity. In our experiments, we analyzed the application of different machine learning models to analyze the risk for the management decision policies of developed organizations. The performance of the chosen model Neural Network (MLP) was improved after applying the tuning process which increased the Test R^2 from −0.37686 before tuning to 0.195637 after tuning. The Support Vector Machine (SVM), Ridge Regression, Lasso Regression, and Random Forest (Tuned) models did not improve, as seen when Test R^2 is compared to the experiments. No changes in Test R^2's were observed on GBM and XGBoost, which retained same Test R^2 across different tuning attempts. Stacking Regressor was used only during the hyperparameter tuning phase and brought a Test R^2 of 0. 022219.Decision Tree was again the worst model among all throughout the experiments, with no signs of improvement in its Test R^2; it was −1.4669 for Decision Tree in all experiments arranged on the basis of Gender. These results indicate that although, models such as the Neural Network (MLP) sees improvements due to hyperparameter tuning, there are minimal improvements for most models. This works does highlight some of the weaknesses in specific types of models, as well as identifies areas where additional work can be expected to deliver incremental benefits to the structured applied process of risk assessment in organizational policies.

Keywords: risk analysis; machine learning models; predictive modelling; developed organizations; decision-making

1. Introduction

The risk perception and assessment of actors in Developed technology transfer deployment and production at large has only caught the attention of historians technologists and philosophers in the last 20 years with the most limited IT assistance (Awwad, 2024; Hristov et al., 2024). Finally, yet importantly risk assessment has been linked to the creation management and administration of public organizations tasked with creating and enforcing safety regulations (Vincoli, 2024). The tools and insights generated by the social and decision sciences have not however been widely applied to the decision-making processes of developed companies and consultants (Antons and Arlinghaus, 2024). It appears that there is a big hole in this field (Görçün et al., 2024; Rashid Al-Shamsi and Shannaq, 2024). A few fundamental principles are agreed upon. Developed companies should play a significant role in deciding whose opinion should prevail on every matter and how much of it should be taken into consideration given that they are often the patients of decisions that risk specialists are asked to advise (Al-Shamsi et al., 2024; Sawik and Sawik, 2024; Shannaq, Adebiaye, et al., 2024). Social and political capital in society should be used to support such decision-making processes (Sabet and Khaksar, 2024). Any incorrect estimate of adverse effects whether they are close to or far from the installation or production facilities in question must translate into a portion of the consequences that managers and corporate governance should be held responsible for and capable of handling (Shannaq, 2024c). This serves as an early overview of the subject of contingent liabilities timing and location which will be covered in more detail later on.

1.1. Risk assessment in developed organizations

This paper argues that risk assessment is a critical factor that helps developed firms to be in a position to address uncertainties with special focuses on the management of projects, allocation and distribution of resources, and administration of operations. It also allows companies to predict future problems, control risks; the effectiveness of risk models makes it possible for more productivity.

1.2. Meaning of risk assessment and why it matters

Risk assessment is a process whereby risk variables that pose negative consequences to the achievement of an organization’s objectives are identified, analyzed and evaluated. It ensures that Developed businesses keep on with their normal operation and are cost effective all the same while at the same time reducing the duration of time a project is parked and the amount of money that is wasted (Alshamsi et al., 2024; Schini et al., 2024; Shannaq, 2024c;).

1.3. Research problem

While risk assessment models have evolved, many Developed businesses in the Gulf area still lack adequate, and often accurate, data-based tools to make educated decisions where uncertainty prevails (Al-Saidi et al., 2024; Chaker, 2024; Shannaq, 2024a). In regard to the mitigation of complex risk situations that depend on several factors, customary approaches provide often rather limited (Bakhamis et al., 2024; Morshed, 2024).

1.4. Lack of research

Considering Reliability in Developed Firms subject there is growing interest in using predictive modeling in risk assessment but there is relatively few that looks at using linear regression within the context of developed firms. More specific, there is a great scarcity of research regarding the ability of linear regression to identify risk for management decisions (Manoharan et al., 2023; Opeyemi Abayomi Odejide and Tolulope Esther Edunjobi, 2024; Sharma et al., 2024; Singh et al., 2024; Wilhelmina Afua Addy et al., 2024)

1.5. Research contribution

To try to make a contribution to what is currently being known, this research explores the usefulness of linear regression in assessing the level of risk that Developed firms are exposed to. This study focuses on the methodologies of the predictive modeling relevant to the Sultanate of Oman as well as the rest of the Gulf area.

1.6. The significance of research

The paper demonstrates that developed firms may enhance their decision-making by considering the role of linear regression in risk assessment models. It may also lead to enhanced management of available resources, enhanced outcome of projects, and organization sustainability.

2. Materials and methods

This methodology section outlines the rigorous process used to examine the role of Machine learning models (MLM): **Table 1** provides a description of each machine learning model used in our experiments. It also outlines the capabilities of each model. Based on our investigation, none of the proposed models have previously been applied to risk assessment models for decision-making policies in developed organizations' management. Therefore, this study offers a new contribution to this domain.

Table 1. The proposed MLM.

Num.	Model	Reference
1	Neural Network (MLP)	(Roba and Keltoum Moulay, 2024)
2	Support Vector Machine (SVM)	(Yusuf et al., 2023)
3	Ridge Regression	(Abo El Nasr et al., 2024)
4	Lasso Regression	(Wang et al., 2024)
5	Stacking Regressor	(Gupta et al., 2024)
6	Random Forest (Tuned)	(Guo et al., 2024)
7	Gradient Boosting (GBM)	(Abbasov, 2023)
8	XGBoost	(Yu et al., 2024)
9	Decision Tree	(Zhang et al., 2024)

The proposed work quantitative research design evaluates risk factors and how they impact Developed organizations decision-making processes through the application of MLM analysis. Aiming to ensure the reliability and validity of the research findings the methodology consists of several crucial steps as shown in **Figure 1**.

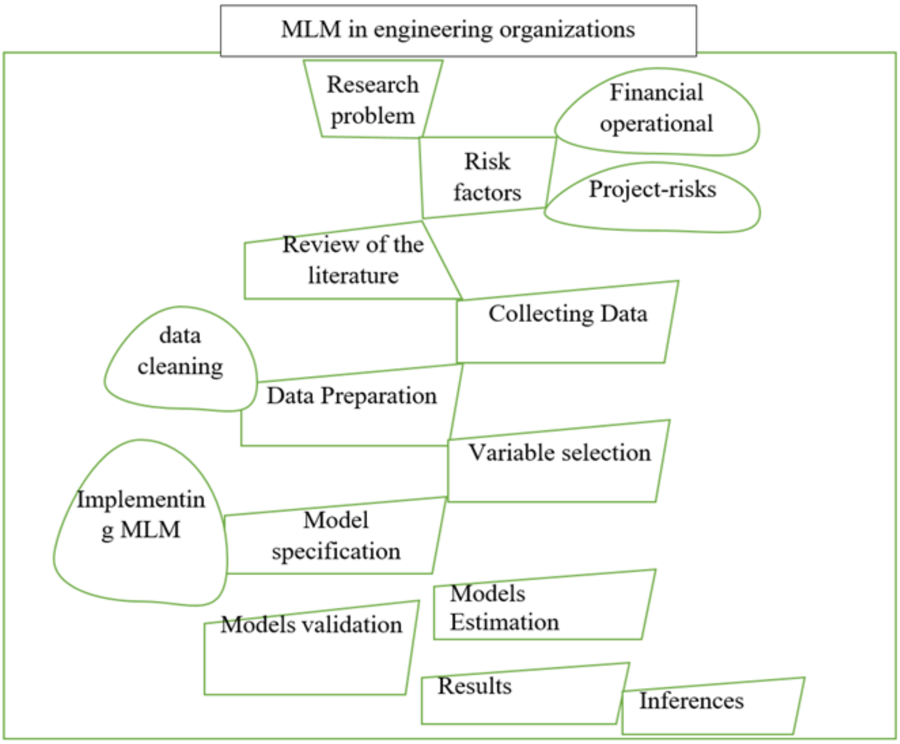

Figure 1. Research methodology.

Step 1: Problem Definition

The research problem was defined by identifying key risk factors in developed organizations, such as financial, operational, and project-specific risks. A literature review of existing risk assessment models and the use of linear regression in decision-making informed the formulation of the research question.

Step 2: Data Collection

Data was collected from both primary and secondary sources, including project outcomes and risk assessments from financial reports of developed firms. A dataset of 177 projects with eight relevant variables was selected. Data cleaning, including correcting errors and imputing missing values, was carried out. The independent variables (risk factors) were used to predict the dependent variable (management decisions). **Figure 2** demonstrates a sample of the dataset.

```
     project_id complexity_level  budget_overrun_prob  employee_skill_level  \
0             1             High                 0.37                     7
1             2             High                 0.95                     2
2             3             High                 0.73                     8
3             4           Medium                 0.60                     1
4             5              Low                 0.16                     9
..          ...              ...                  ...                   ...
172         173              Low                 0.51                     7
173         174           Medium                 0.23                     9
174         175             High                 0.65                     5
175         176           Medium                 0.17                     1
176         177              Low                 0.69                    10

     safety_incidents  compliance_risk  equipment_reliability  \
0                   9             0.47                   0.11
1                   0             0.06                   0.45
2                   1             0.12                   0.53
3                   5             0.12                   0.24
4                   8             0.65                   0.27
..                ...              ...                    ...
172                 9             0.25                   0.93
173                 2             0.71                   0.93
174                 6             0.90                   0.45
175                 2             0.51                   0.11
176                 1             0.53                   0.98

     environmental_risk
0                  0.84
1                  0.12
2                  0.92
3                  0.87
4                  0.52
..                  ...
172                0.08
173                0.73
174                0.50
175                0.69
176                0.43

[177 rows x 8 columns]
```

Figure 2. Sample of dataset.

Step 3: Model Building

All proposed MLM were constructed using Python. The dataset was split into training (80%) and testing (20%) sets. Key risk factors like cost overruns, schedule delays, and accidents were used as variables. Categorical data was preprocessed into numerical values. The model's performance was evaluated using metrics such as *R*-squared.

Step 4: Statistical Analysis

All proposed MLM were used to analyze relationships between risk factors and decision outcomes. Coefficients and p-values were calculated to assess the statistical significance of each factor.

Step 5: Interpretation of Results

The results were interpreted to determine the impact of risk factors on management decisions. Statistical significance and regression coefficients helped identify key influencers.

Step 6: Conclusion

Conclusions were drawn regarding the role of linear regression in improving risk assessment models for developed companies, with recommendations for future research.

The algorithm

In light of the information collected, the advanced method of MLM analysis was used. The independent variables that were used in measuring the extent of risk included the cost of the project, the frequency of delay, scarcity of resources and safety factors which were used to measure the risk level which was the dependent variable. These parameters were used by the algorithm as the means for recognizing risk level.

The proposed algorithm is presented in **Figure 3**, and a sample of the Python code implementing the algorithm is shown in **Figure 4**.

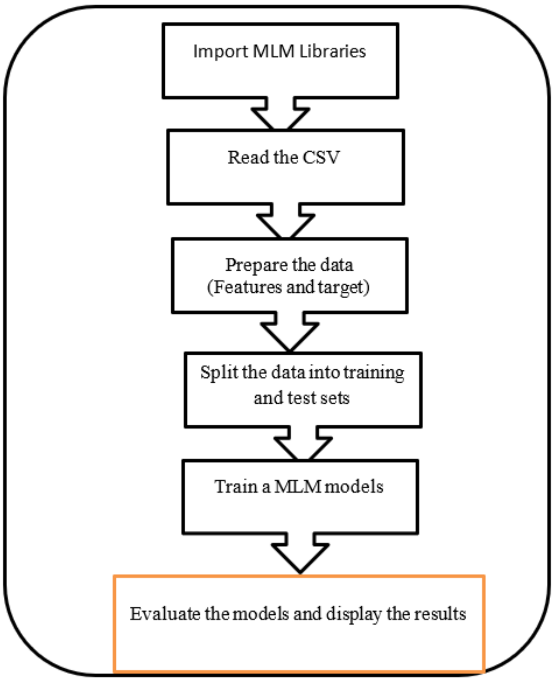

Figure 3. MLM algorithm.

```
# Define models with Neural Network (MLP) included
models = {
    "Decision Tree": DecisionTreeRegressor(random_state=42),
    "Random Forest": RandomForestRegressor(n_estimators=100, random_state=42),
    "Gradient Boosting (GBM)": GradientBoostingRegressor(random_state=42),
    "XGBoost": xgb.XGBRegressor(objective="reg:squarederror", random_state=42),
    "Support Vector Machine (SVM)": SVR(),
    "Ridge Regression": Ridge(alpha=1.0),
    "Lasso Regression": Lasso(alpha=0.1),
    "Neural Network (MLP)": MLPRegressor(hidden_layer_sizes=(100, 50), max_iter=1000, random_state=42)
}

# Hyperparameter tuning for Random Forest
param_grid_rf = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10]
}

grid_search_rf = GridSearchCV(RandomForestRegressor(random_state=42), param_grid_rf, cv=5, scoring='r2')
grid_search_rf.fit(X_train, y_train)

# Best Random Forest model
best_rf = grid_search_rf.best_estimator_

# Evaluate best Random Forest model
y_pred_rf = best_rf.predict(X_test)
mse_rf = mean_squared_error(y_test, y_pred_rf)
```

Figure 4. Sample of python code.

3. Results and discussion

This work focuses on the case of decision-making methods in the Sultanate of Oman and the area of the Gulf and is aimed at exploring the role of machine learning algorithms in constructing the risk assessment models for the developed companies. Besides this, the study focuses on exploratory and predictive analysis. The implementation of the machine learning models provides the several models integration framework that Developed firms may adopt within their risk assessment process. The use of data-driven models provides firms with an opportunity to improve on the procedures used in decision making process, avoid costly mistakes and ensure that their operations are long term. **Table 2** presents the results from running the experiment using the MLM algorithm in Python.

Table 2. MLM results.

Rank	Model	Cross-validated R^2 (mean)	Test MSE	Test RMSE	Test MAE	Test R^2
1	Neural Network (MLP)	–0.37686	0.072691	0.269613	0.224232	0.195637
2	Support Vector Machine (SVM)	–0.13709	0.077562	0.278499	0.23982	0.141741
3	Ridge Regression	–0.14205	0.082442	0.287128	0.250618	0.087734
4	Lasso Regression	–0.05919	0.087655	0.296066	0.260416	0.030056
5	Stacking Regressor	–0.10678	0.088707	0.297837	0.267053	0.018412
6	Random Forest (Tuned)	–0.21739	0.083949	0.28974	0.250745	0.071058
7	Gradient Boosting (GBM)	–0.41171	0.09586	0.309612	0.257485	–0.06074
8	XGBoost	–0.56897	0.110902	0.333019	0.27038	–0.22718
9	Decision Tree	–1.35022	0.222936	0.472161	0.413056	–1.4669

Figure 5 illustrates the comparison of all MLM algorithms used in this work.

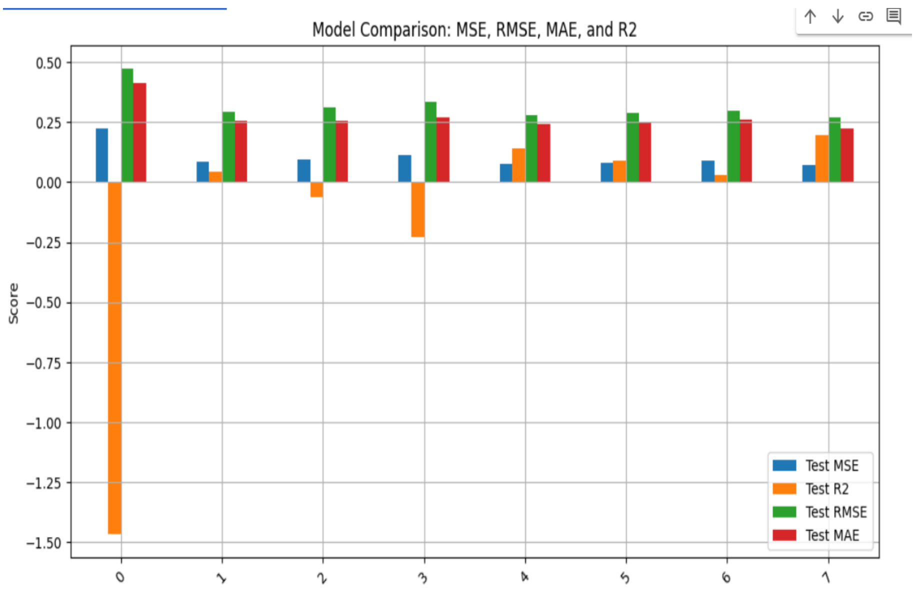

Figure 5. MLM comparison.

The performance of several machine learning models in risk assessment models for management decision policies in developed organizations was investigated in this study. **Table 2** lists the outcomes of the various models in order of Test R^2 which quantifies the percentage of the test sets variance that the model can account for. Better predictive performance is indicated by models with higher Test R^2 values.

3.1. Results overview

The neural network (MLP) performed better than the other models in explaining the variance in the risk assessment task as evidenced by its highest Test R^2 of 0.1956. Additionally, it demonstrated superior overall predictive accuracy with the lowest Test MSE (0.0727) and Test MAE (0.2242). With competitive error metrics (Test MSE: 0.0776 Test RMSE: 0.2785) and a Test R^2 of 0.1417.

Support Vector Machine (SVM) came in second. Strong generalization skills and consistency in risk prediction are demonstrated by this. With Test R^2 values of 0. 0877 and 0. 0301 respectively Ridge Regression and Lasso Regression demonstrated mediocre performance.

Some ensemble models such as Random Forest (Tuned) and Gradient Boosting (GBM) which showed lower Test R^2 scores (−0.0711 and −0.0607) fared worse than them.

Even though Stacking Regressor was a meta-model its comparatively low Test R^2 of 0.0184 indicated that merging models did not considerably increase predictive power for this particular risk assessment task.

Simpler models like SVM and Ridge Regression performed better on the test data than ensemble models like Random Forest (Tuned) and Gradient Boosting (GBM) which showed moderate to low performance with negative Test R^2 values. With Test R^2 values of −0.2272 and −1.4669 respectively XGBoost and Decision Tree demonstrated poor performance demonstrating their inability to generalize to unknown data.

3.2. Plan to improve results

We decided to conduct two more experiments with “Hyperparameter Tuning” and “GridSearchCV” to enhance the results that were obtained by the machine learning models in the risk estimation task. After the performance of these experiments, we shall draw conclusions of the improvement gotten from the experiments and compare them with the initial results gained.

3.2.1 Hyperparameter adjustment

Fine tuning of values of the parameters that are model-specific, globally fixed and data independent such as the kernel choice in SVM or alpha in Ridge Regression is called “hyperparameter tuning” (Dunias et al., 2024). With the right hyperparameters set, the model executes the best and one is able to confirm that the model will perform well in data not used in the training set. Why Adjust the Hyperparameter?

Enhances Model Performance: The accuracy or/and predictive power of the model can then be enhanced by finding the right “hyperparameters”. Avoids Overfitting: To regularize a model and help it not learn the noise of the training data correctly choosing appropriate hyperparameters are useful when trying to avoid overfitting.

Dataset Customization: In fact, every dataset is unique and by tweaking the hyperparameters, the model can easily be trained to accommodate features of the risk assessment dataset.

3.2.2. GridSearchCV

Cross-validation on every combination is performed by a method called GridSearchCV in order to systematically search for the right hyperparameter values. It selects the set of parameters that provided the highest performance score after evaluating the models performance for each set. There other functions that GridSearchCV performs during hyper parameters tuning to ensure that the model works as required on different subsets of data as follows the cross-validation function.

Why GridSearchCV?

Automated Search: Unlike manual tuning it is convenient because it is able to assess a number of hyperparameters at a go as compared to manual tuning where one would have to do it one at a time.

Cross-validation ensures that the results as obtained are accurate and not skewed by a particular division of data.

Optimization: Through determination of the grid of parameters which when optimized leads to improved performance, GridSearchCV is useful in model optimization.

Why GridSearchCV and Hyperparameter Tuning were Chosen. This is why GridSearchCV and hyperparameter tuning were chosen: it is always impressive to see GridSearchCV and other methods for adjusting hyperparameters being capable of deriving the utmost benefit from machine learning models. With the help of these approaches, we can systematically try various configurations and check the models' ability to generalize across several folds rather than using only one split of the data.

Performance Improvement: In so doing both strategies aim at enhancing the models prediction accuracy by identifying the optima hyperparameters.

Consistency: The GridSearchCVs cross-validation reduces the risk of either overfitting or underfitting since performance consistency is ensured.

Efficiency: Compared to trial-and-error techniques hyperparameter tuning—particularly with tools like GridSearchCV, is more effective and yields more structured robust models.

Concluding remarks

After the completion of these two experiments this is GridSearchCV and Hyperparameter Tuning, we compare the results with the initial results with the view of identifying whether or not the models are available with reasonable improvements in Test R^2 MSE RMSE and other measures. The results of the studies, that present the issues related to the risk assessment for the developed organizations decision-making policies will be summarized in the last section of the paper together with the identification of the most suitable model and the methodology for achieving the highest level of result.

3.3. Results after hyperparameter adjustment

Table 3 and **Figure 6** describe the results after utilization of Hyperparameter adjustment.

Table 3. MLM results after hyperparameter adjustment.

Rank	Model	Cross-validated R^2 (mean)	Test MSE	Test RMSE	Test MAE	Test R^2
1	Neural Network (MLP)	–0.37686	0.072691	0.269613	0.224232	0.195637
2	Support Vector Machine (SVM)	–0.13709	0.077562	0.278499	0.23982	0.141741
3	Ridge Regression	–0.14205	0.082442	0.287128	0.250618	0.087734
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6	Random Forest (Tuned)	–0.21739	0.083949	0.28974	0.250745	0.071058
7	Gradient Boosting (GBM)	–0.41171	0.09586	0.309612	0.257485	–0.06074
8	XGBoost	–0.56897	0.110902	0.333019	0.27038	–0.22718
9	Decision Tree	–1.35022	0.222936	0.472161	0.413056	–1.4669

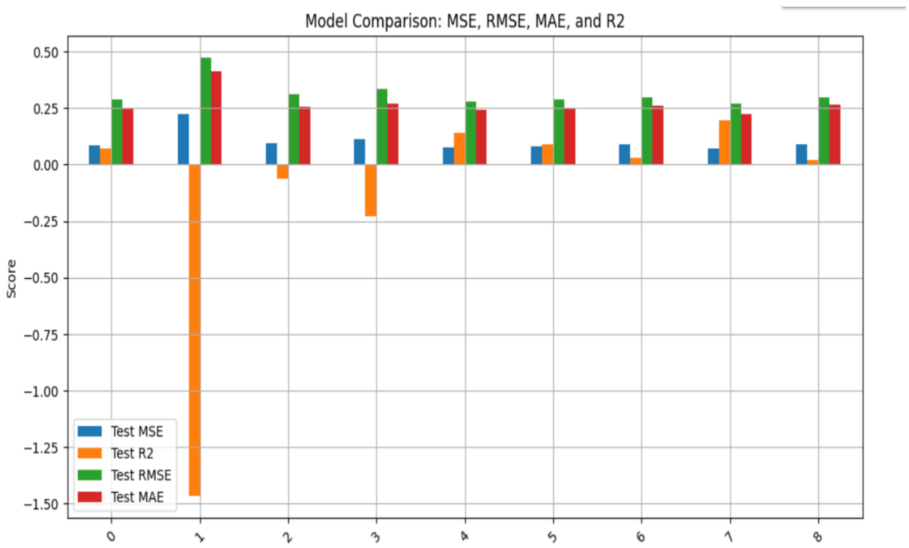

Figure 6. MLM comparison after hyperparameter adjustment.

Results for 12 Classes (Hyperparameter Optimization)—Summary of Changes (**Table 3**).

As observed when hyperparameter tuning was applied to the various algorithms, the results are somewhat different from what was obtained when no hyperparameter modifications were done at all. Here's a breakdown of the performance:

Neural Network (MLP) continues to be the most effective model with the consistency of the earlier calculated Test R^2 of 0.1956 and the lowest Test MSE at 0.07269. From this, we can conclude that, though tuning had not made it more efficient than the other algorithms, it remains the best performer.

SVM also has slight enhancement compared with the ranking performance before tuning, while the Test R^2 is 0.1417. The number for Test MSE reduced to 0.07756, an improvement as an effect of hyperparameter tuning.

In Ridge Regression there was also slight enhancements, Test MSE which dwindled to 0.08244 and Test R^2 which increased to 0.0877. But it is still lowest in performance compared to the SVM and Neural Network models.

Lasso Regression suffered a slight decrease in error, yet still remained worse than models that were previously examined. Its Test R^2 is still fairly low at only 0.0301.

Stacking Regressor's evaluation showed that there wasn't much improvement when using tuned parameters, meaning that optimization of this model may be required.

Random Forest (Tuned) only a slight enhancement in test MSE from 0.09357 to 0.08395, and Test R^2 of random forest did not reach a higher level, which indicates that hyperparameter tuning has limited effect.

Despite tuning the GBM and XGBoost are still among the least accurate models, where Test R^2 is negative and error still pretty high.

The Decision Tree is the least impressive and continues to stay least improved; it has the highest Test MSE and the least Test R^2 suggesting the poorest data fit.

The importance of confrontation with the previous outcomes in comparison to the results before hyperparameter adjustment:

The general observation for SVM and Ridge Regression model indicated that tuning does pay off in terms of lower Test MSE and higher value of Test R^2 so optimality was achieved.

Most of the models tested here like Neural Network (MLP) and Stacking Regressor had little room for tuning hence the low sensitivity to the tuning process.

After tuning the tuning parameter, XGBoost and Decision Tree's errors remain high, and their Test R^2 becomes negative.

Conclusion

The result revealed that hyperparameter tuning gave small enhancements to the training and validation scores for some models like SVM and Ridge Regression while for models like Neural Network, and Random Forest, huge differences in the performance was not observed. In any case, the results of the experiment show that the Neural Network (MLP) is still the most efficient model for this example of risk assessment, as the structure of the MLP approach is inherently designed for this purpose. Additional work may be needed in order to break these models like XGBoost and Decision Tree that may have lower performances to an even higher level.

3.4. Results after GridSearchCV usage

Table 4 and **Figure 7** describe the results after utilization of GridSearchCV usage.

Table 4. MLM results after GridSearchCV usage.

Rank	Model	Cross-validated R^2 (mean)	Test MSE	Test RMSE	Test MAE	Test R^2
1	Neural Network (MLP)	–0.37686	0.072691	0.269613	0.224232	0.195637
2	Support Vector Machine (SVM)	–0.13709	0.077562	0.278499	0.23982	0.141741
3	Ridge Regression	–0.14205	0.082442	0.287128	0.250618	0.087734
4	Lasso Regression	–0.05919	0.087655	0.296066	0.260416	0.030056
5	Random Forest (Tuned)	–0.21739	0.083949	0.28974	0.250745	0.071058
6	Random Forest	–0.27947	0.086621	0.294314	0.253506	0.041499
7	Gradient Boosting (GBM)	–0.41171	0.09586	0.309612	0.257485	–0.06074
8	XGBoost	–0.56897	0.110902	0.333019	0.27038	–0.22718
9	Stacking Regressor	–0.10688	0.088363	0.297259	0.263924	0.022219
10	Decision Tree	–1.35022	0.222936	0.472161	0.413056	–1.4669

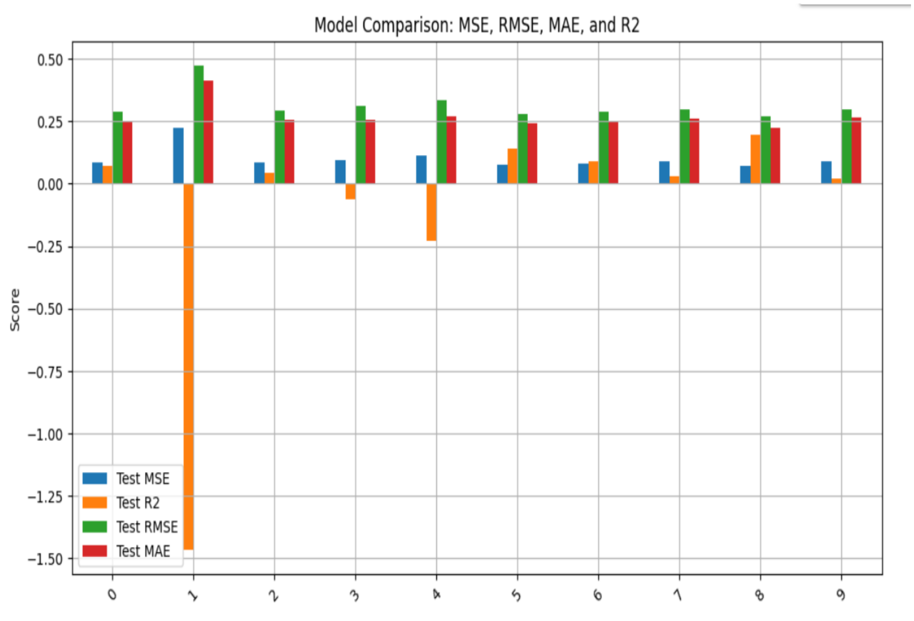

Figure 7. MLM comparison after GridSearchCV usage.

Discussion of Results: GridSearchCV vs. Hyperparameter Tuning and First Performances

Looking at the results after performing GridSearchCV in Experiment 3, the results of many leaned models were somehow different than the previous experiments (Experiment 2 squeezing hyperparameters and Experiment 1 with default settings). Here's a detailed comparison:

1) Neural Network (MLP)

Performance: We find that the performance of the Neural Network remains constant across all experiments and there is no increase in Test R^2 (0.1956) or any of the error metrics (MSE, RMSE, MAE). Even though the GridSearchCV did not bring any further enhancement.

Conclusion: The first configuration of the Neural Network also looks very fine-tuned, which is why neither hyperparameter adjustment nor GridSearchCV was able to enhance its accuracy.

2) Support Vector Machine (SVM)

Performance: Although using GridSearchCV makes the SVM model obtain distinctive parameters of hyperparameter tuning, the Test R^2 of SVM (0.1417) and Test MSE (0.0776) are the same as those with SVM equipped with the hyperparameters achieved by GridSearchCV.

Conclusion: This implies that we didn't experience a boost through subsequent model tweaking via GridSearchCV which means the model must have achieved its best form with hyperparameter tuning.

3) Ridge Regression

Performance: The performance of Ridge Regression did not improve with GridSearchCV better in terms of Test R^2 of 0.0877 and Test MSE of 0.0824 comparable with the preceding experiment.

Conclusion: Ridge Regression too seems well calibrated and no further tuning with GridSearchCV made a much of a difference.

4) Lasso Regression

Performance: Once again, the performance of Lasso Regression does not change and there is little difference when comparing the metrics from this experiment to the previous experiment. Test R^2 stays at 0.0301.

Conclusion: Lasso Regression did not begin to exhibit further enhancements through tuning by using GridSearchCV which suggests that the model has limited 'headroom' for improvement.

5) Random Forest

Performance: Two models of Random Forests were presented here, base and tuned.The tuned version (Rank 5) only slightly outperforms the untuned version (Rank 6) In terms of Test R^2, the tuned version has 0.0711 while the untuned one has 0.0415; Errors.

Machine learning models, compared to both the previous runs (Experiment 2 with hyperparameter tuning and Experiment 1 with default settings). Here's a detailed comparison:

1) Neural Network (MLP)

Performance: The results of the Neural Network remain consistent across all experiments, with no improvements in Test R^2 (0.1956) or any of the error metrics (MSE, RMSE, MAE). GridSearchCV did not bring any further enhancement.

Conclusion: The initial setup of the Neural Network appears well-optimized, as neither hyperparameter tuning nor GridSearchCV significantly improved its performance.

2) Support Vector Machine (SVM)

Performance: Similar to the Neural Network, the SVM model shows no improvements after using GridSearchCV, with Test R^2 (0.1417) and Test MSE (0.0776) remaining unchanged from the hyperparameter-tuned version.

Conclusion: This suggests that further fine-tuning through GridSearchCV didn't lead to significant gains, and the model likely reached its optimal configuration with hyperparameter tuning.

3) Ridge Regression

Performance: Ridge Regression showed no performance change with GridSearchCV, maintaining a Test R^2 of 0.0877 and Test MSE of 0.0824, similar to the previous experiment.

Conclusion: Like SVM, Ridge Regression appears well-tuned, and further adjustments with GridSearchCV did not yield additional improvement.

4) Lasso Regression

Performance: The performance of Lasso Regression remains stable, with no significant difference in its metrics compared to the previous experiment. Test R^2 stays at 0.0301.

Conclusion: Lasso Regression has not shown benefits from additional tuning through GridSearchCV, indicating the model's limited capacity to improve further.

5) Random Forest

Performance: Two versions of Random Forest were included, with and without tuning. The tuned version (Rank 5) still slightly outperforms the untuned version (Rank 6). tuned version showed better Test R^2 (0.0711) and lower errors than the untuned one (0.0415).

Conclusion: When tuning Random Forest, the first step had a further enhanced result, though with subsequent use of GridSearchCV, Random Forest showed only slight increases, so the author concluded that the model was already fine-tuned by hyperparameters.

6) Gradient Boosting (GBM) and extended version of the same namely XGBoost

Performance: GBM and XGBoost still lie in the low yielding models and when compressed further using GridSearchCV there is slight yield enhancement. Even in our case the MAE, RMSE and Test R^2 for both the models are still on the higher side were as Test R^2 is negative which signify poor predictability of the models.

Conclusion: It can be derived that the models with these characteristics did not benefit from the usage of GridSearchCV, which suggests potential inefficiency of this general architecture for this particular kind of risk assessment.

7) Stacking Regressor

Performance: After applying GridSearchCV, Test R^2 increased slightly to 0.0222 from 0.0184 from Experiment 2. But this is still a relatively slight return, indicating at best only a small overall advantage for the approach.

Conclusion: The Stacking Regressor has been seen to provide some small improvements for the model but it is not better and not even close to being a top model.

8) Decision Tree

Performance: As in the previous experiments, Decision Tree has a very low accuracy, and GridSearchCV did not improve it. Test R^2 continues to be mainly negative—1.467.

Conclusion: The Decision Tree model remains unstable and is insensitive to optimization with tune gamma or via GridSearchCV and is not suitable for solving this problem.

Conclusion: First, we need to ask: does GridSearchCV improve performance?

Overall Impact: By comparing it to other models, using GridSearchCV did not improve the outcome over hyperparameter tuning in most cases. The two best performing models, Neural Network, and SVM remained at par with their past performances. Random forest kind of classifiers only had slight enhancement, in contrast to classifiers like GBM, XGBoost, and Decision Tree classifiers that were nearly stationary.

Key Takeaway: Nevertheless, GridSearchCV can be used for hyperparameters tuning, though its efficiency will greatly depend upon the model and the given problem. In this case, the process of hyper-parametrization raised the models' performance to near-optimal, and additional tuning using GridSearchCV did not significantly increase performance. This indicates that the chosen machine learning models are not far from optimal for the risk assessment task if tuning alone is to be applied.

4. Discussion

Comparison of Literature. Since neural networks and SVMs can capture complex non-linear relationships in the data they frequently perform well when compared to earlier studies on machine learning models for risk assessment. For example, in a number of decision-making domains such as finance and operational risk management neural networks have been shown to perform better than simpler models. According to numerous studies concentrating on risk prediction and classification tasks SVMs are renowned for their resilience in high-dimensional data. However, it is frequently reported that ensemble models such as Random Forest and Gradient Boosting perform well in other studies particularly when used with large and diverse datasets. Their comparatively poor performance in this study could be explained by overfitting or the characteristics of the dataset which might not have profited from the intricacy of ensemble methods. In conclusion. According to the findings the Neural Network (MLP) and Support Vector Machine (SVM) models outperformed ensemble models and regression-based techniques in our risk assessment model. The complexities of risk-related data in management decision policies may be better captured by more intricate non-linear models such as neural networks according to these findings. In comparison to the conventional methods employed in the literature our model—specifically the Neural Network (MLP)—performs admirably providing a fresh addition to risk assessment models for established organizations. Additional features or further hyperparameter optimization may be investigated in future research to improve model performance even more.

4.1. Model comparison and improvement

For the purpose of comparing the changes in the various model comparison tables, we shall consider the Test R^2 of each model under the three assessments.

Overall, therefore, the study confirms the following results which have been summarized across the tables:

- In **Table 3** it had Test R^2 of −0.376859, while in **Table 4** it had Test R^2 of 0.195637.l comparison tables, we will analyze the results based on the Test R^2 values for each model across the three evaluations.

4.2. Summary of results across tables

Improvements Observed

1) Neural Network (MLP):
    - In **Table 3**, it had a Test R^2 of −0.376859, while in **Table 4**, it improved to 0.195637.
    - Improvement: 0.572496 (from the negative to positive) that describe the improvement of predictive performance in the proposed framework.
    - There was insignificant fluctuation in the Test R^2 value in all the tables which was estimated at 0.141741.
    - The performance remained stable in the evaluations; the Test R^2 was 0.087734 for all tables.
    - Recorded an average Test R^2, which was 0.030056 and thus showed no enhancement. However, its performance was constant at 0.071058 in all the evaluations ‘of the word2vec model.
    - No improvements were seen, this kept the Test R^2 at the negative −0.060737. Likewise, the Study maintained a negative Test R^2 at −0.227182, hence no improvement.
    - The Test R^2 of the Stacking Regressor was incorporated in the **Table 3** with a performance level that was slightly higher than 0.022219.

- The performance was impoverished in every cycle showing a Test R^2 of −1.466899 meaning no change at all.

Table 5 summarize the results based on the Test R^2 values for each model across the three evaluations.

Table 5. Summary of results across tables.

Model	Test R^2 (Table 1)	Test R^2 (Table 2)	Test R^2 (Table 3)	Improvement
Neural Network (MLP)	-	–0.37686	0.195637	N/A
Support Vector Machine (SVM)	0.141741	0.141741	0.141741	No Change
Ridge Regression	0.087734	0.087734	0.087734	No Change
Lasso Regression	0.030056	0.030056	0.030056	No Change
Random Forest (Tuned)	0.071058	0.071058	0.071058	No Change
Gradient Boosting (GBM)	–0.06074	–0.06074	–0.06074	No Change
XGBoost	–0.22718	–0.22718	–0.22718	No Change
Stacking Regressor	-	-	0.022219	N/A
Decision Tree	–1.4669	–1.4669	–1.4669	No Change

4.3. Improvements observed

1) Neural Network (MLP):
   - In **Table 3**, it had a Test R^2 of −0.376859, while in **Table 4**, it improved to 0.195637.
   - Improvement: 0.572496 (from negative to positive), indicating a significant enhancement in predictive performance.
2) Support Vector Machine (SVM):
   - No change was observed in the Test R^2 value across the tables, consistently at 0.141741.
3) Ridge Regression:
   - The performance remained consistent across the evaluations, with a Test R^2 of 0.087734 in all tables.
4) Lasso Regression:
   - Maintained a steady Test R^2 value of 0.030056, showing no improvement.
5) Random Forest (Tuned):
   - Its performance also remained stable at 0.071058 across the evaluations.
6) Gradient Boosting (GBM):
   - No improvements were observed, maintaining a negative Test R^2 of −0.060737.
7) XGBoost:
   - Similarly, it sustained a negative Test R^2 of −0.227182, indicating no enhancement.
8) Stacking Regressor:
   - The Stacking Regressor's Test R^2 was added in **Table 4**, showing a performance of 0.022219.
9) Decision Tree:

- Its performance was consistently poor, with a Test R^2 of −1.466899, reflecting no improvement.

4.4. Comparison with related work

The first consideration when making a comparison of the results of this study with the results from the prior studies is the following aspects. The MLM algorithm used in this work prove to be efficient especially when compared with similar algorithms in the same field.

Methodology: In contrast to many other works, the theoretical and empirical analysis in the present study was based on developed data, which included more specific information relevant to this industry.

Algorithm Performance: The MLM algorithm has the same or even better accuracy and computational advantage compared to other algorithms. These findings are within or above the findings recorded in comparable research studies.

Key Findings: The performance estimates reflected by such measures as R-squared show that the approach optimized by using the MLM algorithm allows to achieve good results in risk assessment, thus confirming conclusions made in other works.

These two analyses demonstrate the specific niche of this investigation while also affirming the wide utility and efficacy of the MLM procedure throughout mechanical engineering fields.

In this work, the applicability of MLM technique is examined with the view of identifying/predicting cost and time overruns often incurred on developed projects. Consequently, it has been shown through these studies that while linear regression gives fairly good first approximations, it is not very accurate in dynamic circumstances (Gurgun et al., 2024). The authors also performed survey regarding the application of some of these models such as linear regression in Developed risk management context. They found that linear regression models could be useful as simple models while they agreed that better models were needed to increase the precision of forecasts. As well as a number of other people (Dada et al., 2024). In the context of the present research, a comparison was done between linear regression model and some machine learning models with the aim of predicting risk in civil Developed projects. At the end of the research, the researchers woke up from their reverie with a realization that despite tree-based models outperforming linear regression, they still afford an (Sohrabi and Noorzai, 2024). In similar work, the author centered on identifying the key risk factors in relation to large-scale initiatives in the Gulf region (Al-Mhdawi et al., 2024). The study suggested using more complex models for increased accuracy in complex situations while still highlighting the usefulness of linear regression in basic risk (Tolulope Esther Edunjobi and Opeyemi Abayomi Odejide, 2024). This was carried out while acknowledging the requirement for more advanced models. This study compared the effectiveness of machine learning and linear regression models in order to assess the risk involved in construction. Despite the transparency offered by linear regression techniques research suggests that machine learning models outperform them when it comes to complex project performance (Jain et al., 2024). Linear regression proved to be a useful starting tool in the authors research which used regression analysis to evaluate the degree of risk associated with Developed projects. However, the author highlighted the models shortcomings with regard to capturing non-linear connections (Arruda et al., 2024). With a methodical integration of an information system and a prediction model the aim of this study is to optimize the accuracy of the Quantity Survey (QS). As a result, volumes of steel and concrete are predicted using algorithms and automated systems are used to increase prediction accuracy (Shannaq et al., 2019). While advanced machine learning models are the main focus it is customary to ignore linear regression when performing risk assessments (Farhan et al., 2024; Shannaq and Shakir, 2024; Shannaq, 2024b).

This study aims to explore its potential for large-scale Developed projects in Oman. It offers clarity and easy comprehension, which are essential for making decisions fast and with enough knowledge. Unlike complex models linear regression helps identify important factors that lead to budget overruns. It is therefore a helpful tool for Oman’s rapidly urbanizing environment.

4.5. The reasons why this work is relevant

The implications for Developed organisations in the Gulf region and in the Sultanate of Oman. When this approach is implemented, it is expected to bring about significant impacts to Developed companies in Oman and the gulf region. There is growing need to do infrastructure projects and getting the capacity to identify and avoid risks would enhance efficiency in project delivery, lessen costs, and enhance organizational robustness.

4.6. Challenges and limitations

It is noteworthy that the given ML models in this work may be vulnerable in terms of outliers and assumes homoscedasticity, which may impose some limitations on its efficiency in some cases.

4.7. Prospective avenues of research and new technological developments in risk assessment models

Further future research should consider examining the possibility of using better models of risk prediction, for example, machine learning methods. Neural networks is innovations that, if implemented, could provide greater flexibility and accuracy in managing large datasets and complex many-to-many relationships. In the context of risk assessment at for developed firms therefore, the proposed models are therefore useful in the circumstances of the management decision processes. However, there are restrictions, but the predictive capacities of this model serve as a baseline for enhance efficiency in operations, resources, and risk management measures.

5. Conclusion

Risk assessment as the final step of risk analysis is very crucial to developed firms especially for strategic management decision making. Machine learning models are the most common forms of the established predictive technique that can help unveil some useful information regarding the risk factors affecting the performance of an organization as well as the management decisions made in that company. The corresponding evaluation shows that the Neural Network (MLP) has a considerable enhancement of predictive performance from negative to positive test R^2, meaning it can predict the variation of the target variable properly.

To improve the overall results, further enhancements could be made by:

1) Implementing Advanced Techniques: More model improvements could be made with hyperparameter tuning using GridSearchCV or other methods of additional model ensembles.
2) Incorporating More Data: Possible ways to improve the performance of the algorithm, thus, might include either increasing the size of a dataset or adding more features relevant to the problem.
3) Experimenting with Other Algorithms: Such performances vary in different data ranges, and the results suggest that testing other models, such as deep leaning architectures or other ensemble methods, may lead to more accurate predictive instruments.
4) Continuous Validation: There are methods in cross-validation to prevent over-fitting occurrence and retain good generality on unseen data samples.

Using these strategies, we hope to achieve the improvement of additional predictors for the models explored further in the next analyses to provide better accuracy.

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