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Improving Efficiency and Accuracy in Construction Sales Valuation via Random Search Optimization

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Abstract

The valuation of construction project sales depends on various economic variables and indices. While accurate cost predictions support financial planning and risk management, traditional grid-search optimization-based machine learning techniques often demand extensive computational resources for training and optimization, especially when large datasets require comprehensive machine learning models. Recent investigations highlighted that random search optimization can shorten the training time of ensemble machine learning methods. Nevertheless, its effectiveness for construction project cost valuation, especially when examining model accuracy and training time, is still unclear. This research examines the usability of random search optimization for machine learning models in construction project sales valuation and compares it with the standard grid search approach. A large dataset with 103 inputs from 372 construction projects is used as the basis of the investigation. Six different machine learning models are designed and optimized under grid search and random search approaches to evaluate training time and predictive accuracy. The study results indicate that random search optimization cuts training time by up to 70% and preserves a high level of accuracy, with the best-performing model achieving an R^2 of 0.98 on the test set. These findings highlight random search optimization as a strong alternative to grid search, providing significant computational savings without harming model performance. The study offers guidance on effective hyperparameter tuning methods that may facilitate scalable and budget-friendly predictive models for construction project valuation.

Keywords: Real Estate; Construction Sales Valuation; Economic Variables and Indices; Machine Learning Optimization.

1. Introduction

Real estate is often selected in investment planning because it has strong potential for long-term income and stability [1-4]. Property values depend on many different factors, especially economic and financial conditions, that change over time [5-7]. When cities expand and population increases, the need for accurate housing estimates becomes more important. These estimates help in planning for demand, supply, investment, and even taxes [8-14]. Housing price forecasting has gained attention in recent years. Several studies proposed forecasting methods to help decision-making in real estate [15, 16]. Ibisola et al. [17] pointed out that valuation must be clear and consistent in order to avoid errors in price prediction. Although many models were suggested in the past, making a single method that works well in all cases is still difficult because different social and economic conditions always interact with the prediction problem [18, 19]. For this reason, recent works started to apply advanced models that use computing algorithms and data processing techniques [20-25]. Machine learning has become more used for this kind of forecasting in different countries. For instance, Jafary et al. [26] studied different machine learning and deep learning models and showed how these can use

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many property features to estimate land values. Gurmu & Miri [27] used machine learning regressions to estimate the cost range in construction, which can also help with predicting real estate value. Sammour et al. [28] worked on housing demand prediction in Jordan, which helps developers prepare for future projects. In another example, Calainho et al. [29] introduced a method for real estate price indexing using machine learning, which adds more support for automated valuation. Some studies took a larger-scale view in property modeling. Jafary et al. [30] built a macro-level property valuation model using steps like spatial imputation and machine learning together. Özalp and Akıncı [31] compared different tree-based algorithms and showed which ones give better price predictions for housing. Mathotaarachchi et al. [32] discussed machine learning methods that give better forecasts than basic models, while Hoxha [33] tested different machine learning techniques in Prishtina and compared their accuracy. Other studies worked on explainable models, which make it easier to understand how the prediction happens. For example, Gunes [34] applied model-agnostic machine learning to real estate valuation and discussed its usability. Areo [35] discussed how machine learning is becoming more used in real estate and what its possible applications are. Some papers focus on combining data with building systems.

Su et al. [36] introduced a model where machine learning and building information modeling are used together for valuation. In another research, Baur et al. [37] showed how property descriptions can help improve automated valuation using machine learning methods. Neural network models are another way to estimate housing prices. Rafiei and Adeli [38] developed a model that can estimate the sale prices of houses. Kim et al. [39] applied a hybrid approach using neural networks and genetic algorithms for construction cost prediction. Other researchers also explored neural-based methods in different real estate and infrastructure applications [40, 41]. Jang et al. [42] studied deep learning models to check bankruptcy risk in construction. Elalem et al. [43] worked on sales forecasting with neural models. Saha et al. [44] applied machine learning in bond valuation, which is outside of real estate but still shows how financial forecasting is now moving to intelligent models. In general, among these approaches, explainable machine learning models remain good methods for such problems due to their potential interoperability with prediction accuracy. However, using grid search for optimizing explainable machine learning models typically requires a lot of computing power, especially with large datasets that include many input features. Some recent studies mention that random search can reduce the training time of ensemble models. However, its applicability to machine learning models when predicting sales values of construction projects using economic variables and indices is still questionable. This includes the effect of optimization methods on both training speed and prediction accuracy. This study uses random search to train different machine learning models for this task. In this regard, six machine learning models are developed and trained with random search, while grid search is used for comparison to validate the applicability of the random search approach to a feasible benchmark. The study adopts a dataset of 372 completed construction projects with 103 input factors. Thereafter, a comparison is made between the models based on how long they took to train and how accurate they are. In general, showing how random search can save computing resources without reducing accuracy can help in developing machine learning models that are faster and can be used for real estate forecasting on a larger scale.

2. Research Methodology

This section provides a comprehensive discussion of the various machine learning models utilized in this study, along with their mathematical formulations. While artificial neural networks have been widely used for predicting housing prices in the real estate sector, the efficiency of different machine learning models in estimating construction project sales valuation remains a critical area of investigation. A key focus of this study is the comparative evaluation of hyperparameter optimization techniques, specifically random search optimization and grid search optimization, to assess their impact on model training efficiency and predictive accuracy. By benchmarking multiple models against these optimization techniques, this research aims to determine whether random search can significantly reduce computational time without compromising predictive performance. The overall methodology adopted in this study is illustrated in Figure 1.

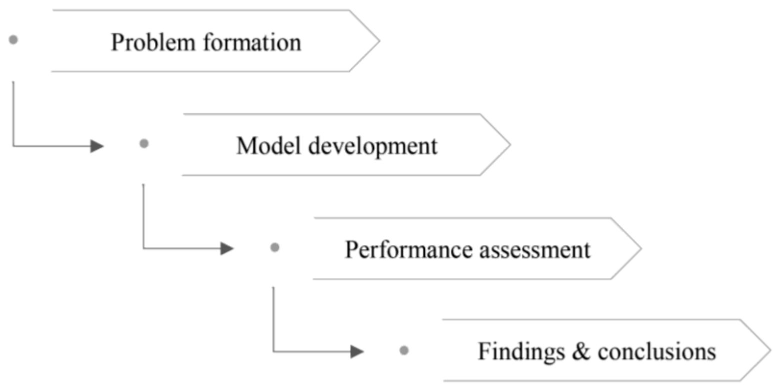

Figure 1. Illustration of the general research methodology adopted in this study

2.1. Adopted Database

All machine learning models in this investigation rely on a dataset developed by Rafiei & Adeli [38] that reflects various elements affecting the profitability of 372 completed residential construction projects. This dataset provides 103 non-real-time input features grouped under physical and financial (P&F) variables and economic variables and indices (EV&Is), both of which strongly influence project sales valuation. Physical and financial variables address project-specific details such as site location, total floor area in square meters, lot area, and the initial estimated construction cost. They also include cost breakdown parameters like estimated cost per square meter and its adjusted equivalent. Additional variables include construction duration measured in quarters, months, or weeks, as well as the price per square meter of the residential unit at project inception. These factors shape financial planning and market positioning, forming an essential foundation for machine learning approaches. The second category, economic variables and indices, incorporates macroeconomic and financial indicators affecting real estate and construction markets.

The dataset covers the number of building permits, total subcontractor contract values (adjusted to a base year), and the producer price index (WPI) for building materials. It also features total floor areas for issued permits, cumulative liquidity in millions of dollars, and private-sector investments in new buildings to reflect market activity. Other relevant financial indicators include the land price index for a base year, the quantity and value of bank loans issued over a designated period, and the corresponding interest rate. Information on average construction costs borne by the private sector at both the start and completion of projects is also provided, expressed in millions of dollars per square meter. Exchange rate variations are covered by including official and unofficial rates compared to the U.S. dollar. Inflation-related data includes the consumer price index (CPI) for a base year and the CPI for housing, water, fuel, and power, factors that directly affect purchasing power and cost changes. Stock market indices, city population, and gold price per ounce are part of the dataset to capture broader economic stability. Integrating these project-based details and macro-level financial indicators helps generate more accurate valuations of construction project sales. This combined dataset offers a broad representation of the variables shaping project profitability, which is crucial for assessing how hyperparameter tuning with random search and grid search impacts predictive performance in construction project sales valuation.

2.2. Machine Learning Models

Machine learning models have become prominent in predictive analytics because they recognize patterns between input features and target outputs in historical data. In construction project sales valuation, these models estimate future sales values by analyzing data patterns associated with economic and project-specific factors. The approach selected for modeling directly affects both predictive precision and computational efficiency. This section outlines six models used in the study: Decision Tree (DT), Random Forest (RF), Extremely Randomized Trees (ETR), Adaptive Boosting (AdaBoost), Histogram Gradient Boosting (HGB), and Stochastic Gradient Boosting (GB).

2.2.1. Decision Tree (DT)

Decision Tree (DT) is frequently applied in classification and regression. It partitions the dataset recursively based on the most informative features, creating a hierarchy where each internal node involves a feature-based decision, each branch indicates a decision outcome, and each leaf node holds the predicted value. The method typically aims to minimize impurity at each node, often measured with Gini impurity, entropy, or mean squared error for regression. One advantage of DT is its transparent structure, which clarifies how predictions are made. Nonetheless, DT can overfit when deep trees are formed. Pruning or restricting tree depth can mitigate overfitting, and ensemble strategies often further improve performance. Despite these challenges, DT remains a strong baseline in predictive modeling, especially as a foundational element for ensemble methods.

2.2.2. Random Forest (RF)

Random Forest (RF) extends the decision tree approach by generating multiple decision trees and merging their outputs to increase accuracy and stability. A single decision tree can exhibit high variance and overfitting, but RF lowers this risk through bootstrapped sampling of training data, which produces different subsets for each tree. The algorithm also introduces feature randomness by picking a random subset of features at each split, reducing correlation among trees and bolstering the ensemble's predictive capacity. In regression, RF typically averages the outputs of the individual trees, while classification problems generally adopt a majority voting mechanism. RF handles high-dimensional data effectively and tolerates noise or missing entries. However, training and inference may become time-consuming if a large number of trees is used.

2.2.3. Extremely Randomized Trees (ETR)

Extremely Randomized Trees (ETR), sometimes called Extra Trees, follows an ensemble structure similar to random forest but increases randomness in its splitting process. Each tree is built on a subset of training data, yet ETR picks split thresholds at random rather than optimizing them. This procedure reduces computation because searching for the best split is unnecessary. Enhanced randomness lowers the chance of overfitting, as trees become less sensitive to noise.

However, random splits can lead to less precise partitioning, causing a slight drop in accuracy in some scenarios. ETR still performs well in regression and classification tasks, especially when hyperparameters are tuned to balance bias and variance.

2.2.4. Adaptive Boosting (AdaBoost)

Adaptive Boosting (AdaBoost) combines multiple weak learners, usually decision stumps, in a sequential manner. Each learner tries to correct the errors made by previous ones. Models that misclassify more data receive increased focus in the subsequent round by assigning higher weights to those points. This mechanism pushes the model to handle harder examples over iterations. Final predictions emerge from a weighted sum of all weak learners, where weights reflect each learner's accuracy. Although AdaBoost often delivers high accuracy with shallow learners, it can be sensitive to noisy data and outliers, because they may gain undue influence if repeatedly misclassified.

2.2.5. Histogram Gradient Boosting (HGB)

Histogram Gradient Boosting (HGB) refines the gradient boosting framework by compressing continuous features into histograms. Traditional gradient boosting trains decision trees iteratively, adjusting model weights according to gradient information. HGB accelerates this process through histogram binning, which reduces the candidate split points and saves memory. The method retains strong predictive performance on large datasets, thanks to its efficient use of regularization strategies like early stopping and feature importance pruning. Careful tuning of histogram parameters is needed to avoid losing important information, but HGB can achieve a suitable balance between speed and accuracy in regression and classification.

2.2.6. Stochastic Gradient Boosting (GB)

Stochastic Gradient Boosting (GB) adds randomness to the traditional gradient boosting approach. Gradient boosting trains trees sequentially to reduce errors, and stochastic GB introduces two forms of randomness: selecting a random sample of training data for each tree and sampling features randomly at each split. This diversification can reduce overfitting and computational cost, which is particularly helpful with large datasets. Nonetheless, hyperparameter tuning must manage the trade-off between randomness and accuracy. Excessive randomness may hamper learning of relevant patterns, while too little randomness might cause overfitting. Stochastic GB remains a popular choice in many predictive tasks due to its solid generalization capability and moderate computational demands.

2.3. Grid Search and Random Search Optimization of Machine Learning Models

Grid search systematically examines every combination of specified hyperparameter values in a given search space. Each combination undergoes cross-validation, and the best set of hyperparameters is chosen based on a designated performance metric. Though comprehensive, this approach becomes time-consuming in high-dimensional searches or when data sizes are large since training time escalates sharply with more parameters or candidate values. Random search provides a more efficient alternative by sampling hyperparameter values randomly from predefined ranges. This dramatically reduces computational effort and still identifies strong hyperparameters, as not all combinations need to be checked. Research suggests that random search often reaches near-optimal solutions much faster than grid search because it avoids exhaustive evaluations of less important regions of the search space. It also has a higher likelihood of finding better settings in situations where only a subset of hyperparameters substantially affects model quality. While random search cannot guarantee an absolute optimum, it delivers significant time savings without marked losses in accuracy. In this study, random search is compared with grid search to determine if similar predictive accuracy can be obtained at a lower computational cost, which is particularly relevant for large or complex datasets. Table 1 contrasts the two methods in terms of search technique, computational load, efficiency, and scalability.

Table 1. Grid search and random search optimization techniques

Criteria	Grid Search	Random Search
Search Method	Exhaustive search through all parameter combinations	Randomly selects parameter combinations
Computational Cost	Exponentially increases with number of parameters	Evaluates a subset of possible combinations
Efficiency in High-Dimensional Spaces	Computationally expensive	Efficiently explores search space
Probability of Finding Optimal Parameters	Within predefined search range	Depends on iterations
Coverage of Search Space	Fixed and structured	Unstructured and broader
Suitability for Large Datasets	Can be slow	Scales better
Flexibility in Parameter Ranges	Limited to predefined values	Highly flexible
Training Time	Long	Shorter
Scalability to Complex Models	Challenging for complex models	More adaptable to complex models
Ease of Implementation	Straightforward but slow	Easy and faster

2.4. Model Development and Hyperparameters Tunning

Model development involved data preprocessing, selection of algorithms, and hyperparameter tuning. The dataset, which includes numerous economic variables and project-specific characteristics, was split into training and testing sets at an 80:20 ratio. This design ensures that final performance measurements reflect a fair estimate of generalization. The algorithms considered in this research include DT, RF, ETR, AdaBoost, HGB, and GB. Each has a set of hyperparameters, such as the number of estimators, learning rate, tree depth, and regularization factors, that must be configured for optimal performance. GridSearchCV and RandomizedSearchCV from standard libraries handled hyperparameter tuning, enabling a direct comparison between the exhaustive approach and a stochastic alternative. Both methods rely on cross-validation for model evaluation. Grid search evaluates every combination of hyperparameter values in a predefined range, while random search selects random points from that range, often achieving near-optimal results at significantly lower computational cost. Each algorithm was optimized using both methods, and the best hyperparameters were chosen for further evaluation. The chosen regression metrics included the coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute error (MAE). Separate evaluations of training and testing sets captured the potential for overfitting. Computation times were recorded to quantify potential speed gains. Models optimized with the best hyperparameters were then tested on unseen data, and actual vs. predicted outcomes were compared for additional clarity. Final model selection prioritized accuracy, efficiency, and robust generalization. Conclusions drawn from these outcomes highlight whether random search can effectively lower training effort while preserving predictive quality in construction project sales valuation applications.

3. Results and Discussions

As discussed before, explainable machine learning models are considered suitable for construction sales valuation since they can provide good prediction accuracy and can be used with other systems. However, when grid search is used to tune these models, it usually needs high computing power, especially when working with large datasets that include many input variables. Some new studies mention that random search can make the training faster in ensemble models. Still, there is doubt about how well it can be used in machine learning models when predicting sales values in construction projects where many economic indicators and indices are involved. This includes how the optimization method affects both the training time and how accurate the predictions are. In this study, random search is used to train different machine learning models for this kind of problem. Six machine learning models are built and trained with random search, and grid search is used as a comparison method to check if random search gives similar results. The study works with a dataset that includes 372 finished construction projects and uses 103 input features. Then, the models are compared based on how fast they train and how accurate they are. The dataset includes several variables that represent the economic, structural, and temporal factors affecting construction sales prices, which makes the modeling task more complex.

In general, the findings of this study present a detailed comparison of predictive performance, error metrics, and computational efficiency across various machine learning models tuned with Grid Search and Random Search. Both hyperparameter tuning methods exhibit comparable accuracy, while Random Search reduces training time without lowering performance. The evaluation metrics (R^2, RMSE, MAE, and training time) were applied to DT, RF, ET, AdaBoost, HGB, and GB. Figure 2 shows measured versus predicted values for each model in training and testing, using scatter plots to map predictions against actual outcomes. Each subplot focuses on one machine learning model and highlights a tight clustering of data points along the diagonal line, confirming reliable predictive capabilities. Nearly identical results from both tuning strategies imply that Random Search successfully identifies suitable hyperparameters without exhaustive trials, which is valuable for models requiring significant computational resources. These findings are consistent across different models, which suggests that Random Search can be used in a broader range of regression-based valuation problems in the construction domain. It may also be suitable when quick deployment is needed without reducing model accuracy.

The R^2 values, which indicate how well each model explains variance in the dataset, are summarized in Figure 3. The bar charts display training and testing R^2 under both tuning techniques, followed by a third chart illustrating the percentage change in R^2. Across the models, differences between Grid Search and Random Search remain minimal. ET and GB reach the highest R^2 values, approximately 0.98 in testing, while RF and HGB also attain strong performance exceeding 0.94. The percentage change in R^2 falls below 0.5% in most cases, confirming that Random Search preserves high accuracy while helping to conserve computational effort. This result becomes more important when using limited hardware or when frequent model updates are needed. Also, since a small variation in R^2 may not always lead to noticeable differences in actual predictions, the result supports using Random Search in practice. These outcomes show that even for complex regression problems with many input variables, Random Search still manages to maintain high performance.

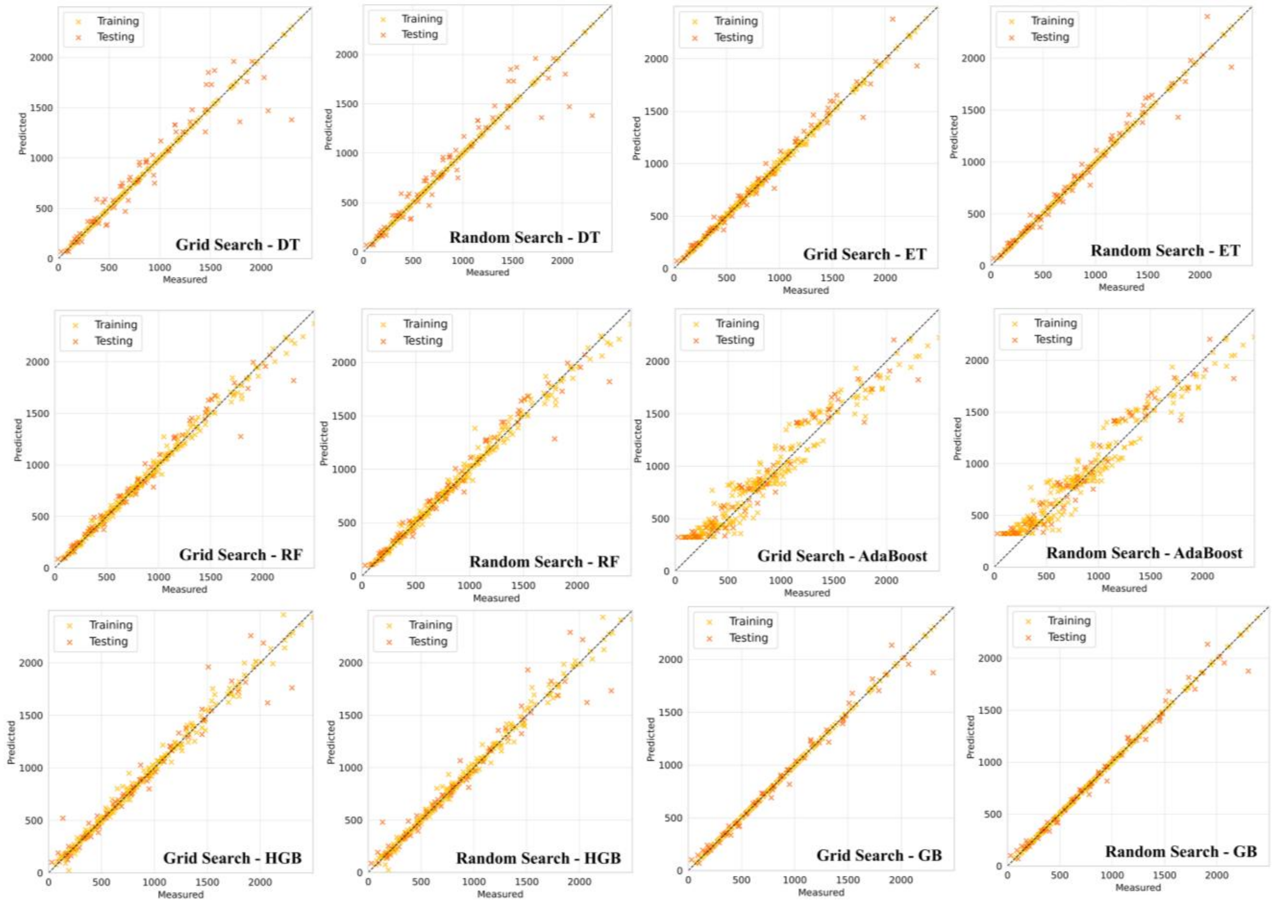

Figure 2. Measured versus predicted plots for the training and testing results of the investigated results

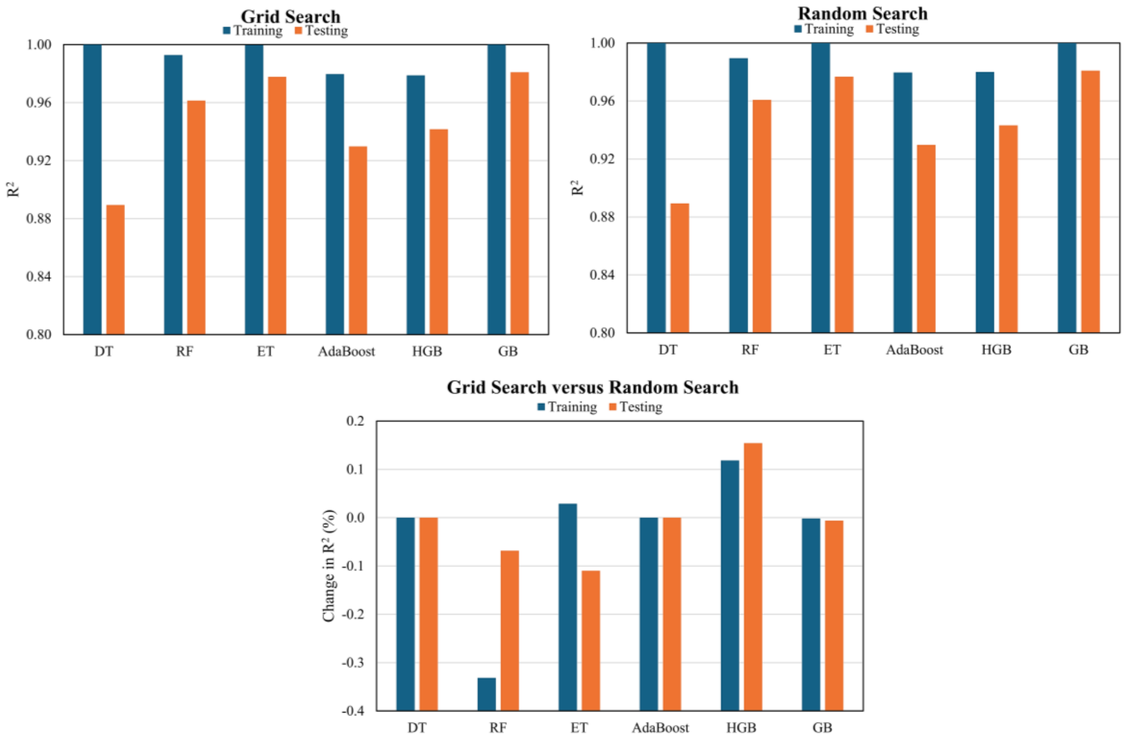

Figure 3. R^2 of the investigated machine learning models

Figures 4 and 5 display RMSE and MAE for the examined models, giving an overview of the magnitude and average magnitude of prediction errors, respectively. Differences in RMSE between Grid Search and Random Search are generally minor, except for GB, where the training RMSE increases considerably with Random Search even though it is still very low in value. This shift does not cause a marked decline in testing performance, implying that hyperparameter variations may influence training stability but do not undermine model generalization. RF, ET, and HGB maintain low RMSE values, reflecting dependable forecasts for construction project sales valuation. MAE outcomes mirror these observations, as shown in Figure 5.

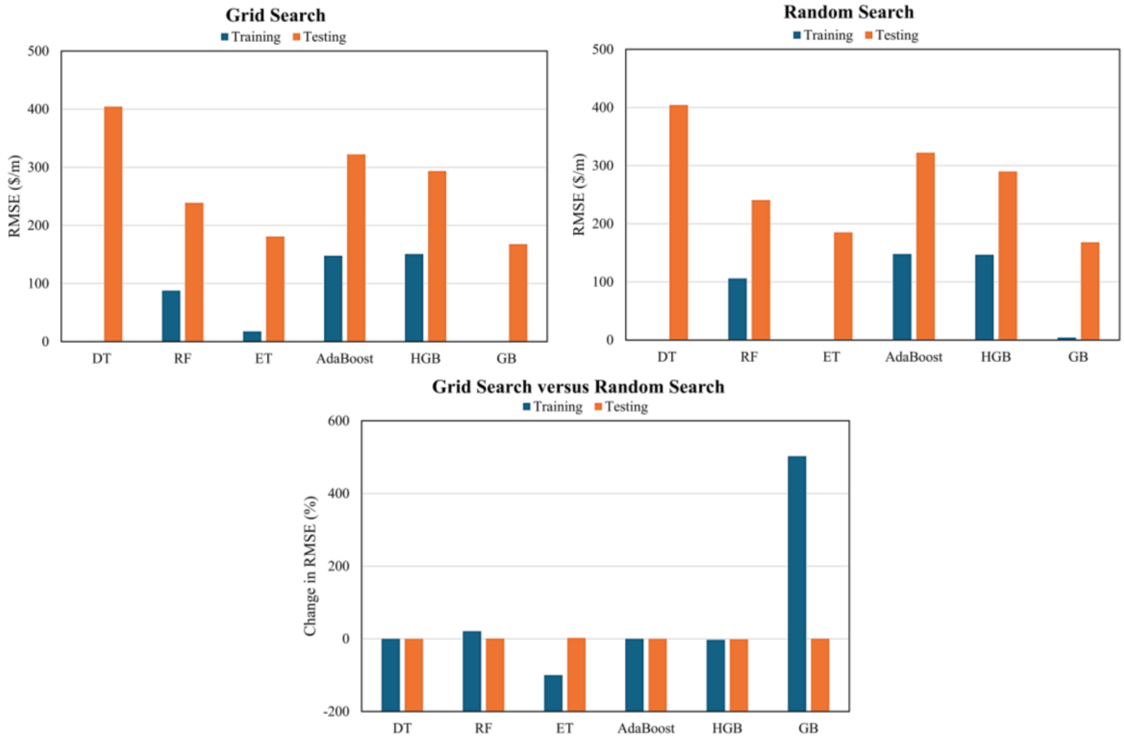

Figure 4. RMSE of the investigated machine learning models

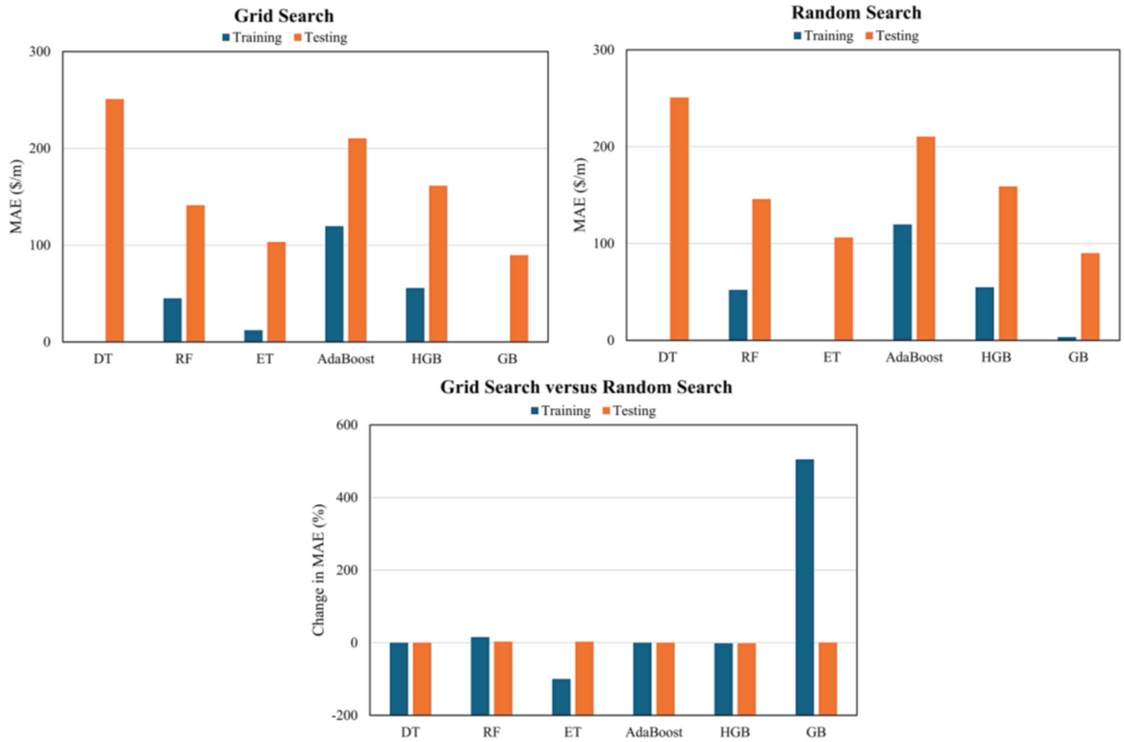

Figure 5. MAE of the investigated machine learning models

The percentage change in MAE is small for most models, indicating that both tuning methods achieve comparable accuracy. Although GB experiences a significant uptick in MAE during training, the testing phase remains steady, suggesting that complex models may be sensitive to hyperparameter adjustments, yet real-world predictive ability remains consistent. These results further support the argument that small variations in tuning may slightly affect the internal behavior of the model during training but do not affect the usefulness of the model when making future predictions. Also, this consistency is important in construction valuation, where wrong forecasts may affect planning and investment decisions. One of the most important findings involves shorter training durations under Random Search, as depicted in Figure 6. The left bar chart lists absolute training times in seconds for each model, and the right bar chart reports percentage reductions achieved through Random Search. Improvements occur with DT (70% faster) and RF (68.52% faster). ET and HGB see gains of 51.47% and 63.28%, respectively. Adaptive Boosting shows a modest reduction of 16.76%, yet still benefits from the method's efficiency. These reductions in time can help practitioners who do not have access to advanced hardware or need to retrain models often. Especially in industry settings where deadlines are short, or system resources are shared, faster training can make the entire workflow more manageable. While accuracy is good overall, the time savings give more flexibility and allow for repeated testing and fine-tuning to reach the best results. Even if the gains in speed are not uniform across all models, the general pattern shows that Random Search brings consistent efficiency. This makes it a useful option in cases where both predictive accuracy and training speed are important at the same time.

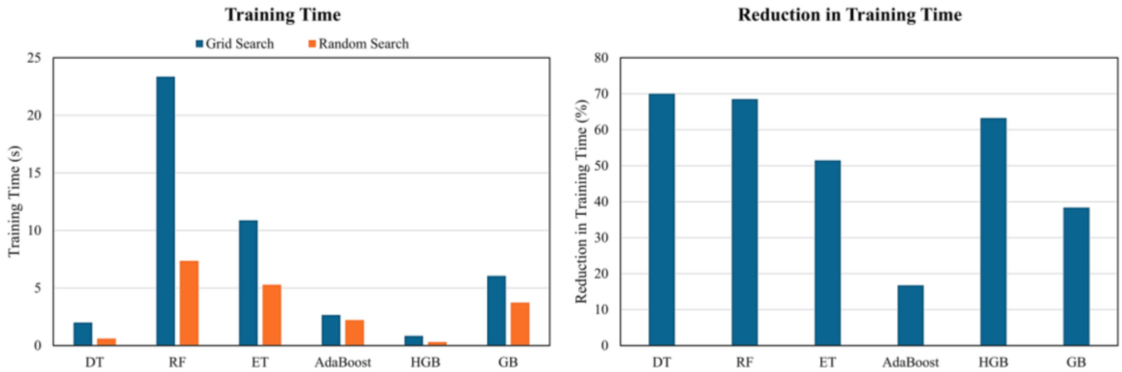

Figure 6. Training time analysis of the investigated machine learning models

Overall, these results prove the applicability of machine learning models for construction project sales valuation. This observation aligns well with existing studies in the previous studies [25, 32, 37, 38]. Moreover, these outcomes confirm that Random Search accelerates model development while preserving similar accuracy levels, making it a more computationally efficient approach for hyperparameter tuning in machine learning. The comparison of Grid Search and Random Search in construction project sales valuation reveals that both yield nearly the same predictive performance, as shown by minimal differences in R^2, RMSE, and MAE. In this regard, the Gradient Boosting model with random search gave the highest accuracy, while the Random Forest model with random search trained faster than the others. Exhaustive hyperparameter searches appear unnecessary for achieving optimum results, given the significant time savings of Random Search. In some instances, training time is cut by as much as 70%, which strongly favors Random Search in large-scale scenarios. Moving from Grid Search to Random Search delivers substantial reductions in training time while maintaining high accuracy, making it a suitable choice for real-world machine learning tasks in construction sales valuation. Ultimately, it is worth noting that the results of these training times are inherently affected by the computing hardware. Nevertheless, the pattern in saving computational time is expected to be consistent in general.

4. Conclusion

This investigation assessed random search optimization for machine learning models aimed at forecasting construction project sales using economic variables and indices. Earlier publications indicated that random search can streamline training in general machine learning contexts, but its impact on this domain was not clearly established. Six models were tested with both grid search and random search to explore whether random search preserves prediction accuracy while significantly cutting training time. Findings confirm that random search achieves predictive accuracy that is similar to grid search, with R^2 values reaching 0.98 for the best model. Training time declined by as much as 70% in some instances, such as the Random Forest. Models optimized under random search also showed close alignment of measured and predicted values, implying minimal effect on generalization. Ensemble methods, including Random Forest, Extremely Randomized Trees, and Histogram Gradient Boosting, showed benefits from the faster tuning process. In particular, the best machine learning model combined with the random search was the Gradient Boosting model in terms of accuracy and the Random Forest in terms of training time. Therefore, adopting random search presents a strong option for construction firms, financial analysts, and policymakers seeking swift and reasonably accurate real estate valuations and project pricing strategies. Although the dataset in this study was limited to 372 construction projects and 103 input features, the results suggest that random search can deliver substantial computational advantages in bigger or more complex settings. Other optimization strategies, such as Bayesian methods or genetic algorithms, could offer further improvements. Future work may also look at real-time economic indicators and deep learning architectures to broaden these findings for dynamic market conditions. Addressing these aspects can strengthen the scalability and adaptability of machine learning-driven valuation models in the construction field.

5. Declarations

5.1. Author Contributions

A.K. and Y.Z. contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

5.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

5.4. Conflicts of Interest

The authors declare no conflict of interest.

6. References

[1] Peter, N. J., Okagbue, H. I., Obasi, E. C., & Akinola, A. O. (2020). Review on the Application of Artificial Neural Networks in Real Estate Valuation. International Journal of Advanced Trends in Computer Science and Engineering, 9(3), 2918–2925. doi:10.30534/ijatcse/2020/66932020.

[2] Kaklauskas, A., Zavadskas, E. K., Lepkova, N., Raslanas, S., Dauksys, K., Vetloviene, I., & Ubarte, I. (2021). Sustainable construction investment, real estate development, and covid-19: A review of literature in the field. Sustainability (Switzerland), 13(13), 7420. doi:10.3390/su13137420.

[3] Tsou, W. L., & Sun, C. Y. (2021). Consumers' choice between real estate investment and consumption: A case study in taiwan. Sustainability (Switzerland), 13(21), 11607. doi:10.3390/su132111607.

[4] Sorinola, M. (2024). Building Climate Risk Assessment Models For Sustainable Investment Decision-Making. International Journal of Engineering Technology Research & Management, 8(1).

[5] Duca, J. V., Muellbauer, J., & Murphy, A. (2021). What drives house price cycles? International experience and policy issues. Journal of Economic Literature, 59(3), 773–864. doi:10.1257/JEL.20201325.

[6] Rahmawati, D., Rahadi, R. A., Putri, A. D., Tinggi, S., Ekonomi, I., & Bandung, E. (2021). The Current State of Property Development in Indonesia During the Covid-19 Pandemic. International Journal of Innovation, Creativity and Change, 15(7), 1-19.

[7] Banka, M., Dao, M. T. H., & Minh, D. T. (2022). Analysis of business strategy of real estate developers in Vietnam: the application of QSPM matrix. International Journal of Multidisciplinary Research and Growth Evaluation, 3(1), 188-196.

[8] Kumar, K., & Singh, D. D. P. (2023). Assessing the dynamics of urbanization: A comprehensive review of associated risks and mitigation strategies. Journal of Research in Infrastructure Designing, 6(3), 1-10.

[9] Kiviaho, A., & Toivonen, S. (2023). Forces impacting the real estate market environment in shrinking cities: possible drivers of future development. European Planning Studies, 31(1), 189–211. doi:10.1080/09654313.2022.2121604.

[10] Kresse, K., & van der Krabben, E. (2022). Rapid urbanization, land pooling policies & the concentration of wealth. Land Use Policy, 116, 106050. doi:10.1016/j.landusepol.2022.106050.

[11] Frew, J., & Jud, G. D. (2003). Estimating the value of apartment buildings. Journal of Real Estate Research, 25(1), 77–86. doi:10.1080/10835547.2003.12091101.

[12] Limsombunc, V., Gan, C., & Lee, M. (2004). House Price Prediction: Hedonic Price Model vs. Artificial Neural Network. American Journal of Applied Sciences, 1(3), 193–201. doi:10.3844/ajassp.2004.193.201.

[13] Kang, Y., Zhang, F., Peng, W., Gao, S., Rao, J., Duarte, F., & Ratti, C. (2021). Understanding house price appreciation using multi-source big geo-data and machine learning. Land Use Policy, 111, 104919. doi:10.1016/j.landusepol.2020.104919.

[14] Jiménez-Jiménez, S. I., Ojeda-Bustamante, W., Marcial-Pablo, M. D. J., & Enciso, J. (2021). Digital terrain models generated with low-cost UAV photogrammetry: Methodology and accuracy. ISPRS International Journal of Geo-Information, 10(5), 285. doi:10.3390/ijgi10050285.

[15] Karadimos, P., & Anthopoulos, L. (2024). A taxonomy of machine learning techniques for construction cost estimation. Innovative Infrastructure Solutions, 9(11), 420. doi:10.1007/s41062-024-01705-0.

[16] Skitmore, M., Irons, J., & Armitage, L. (2007). Valuation accuracy and variation: a meta-analysis. Proceedings from the PRRES Conference 2007, 21-24 June, 2007, Perth, Australia.

[17] Ibisola, A. S., Durodola, O. D., Oluwatobi, A. O., Oni, A. S., & Peter, N. J. (2019). Factors contributing to the valuation of arts and artifacts in Ogun State, Nigeria. International Journal of Civil Engineering and Technology, 10(1), 2224–2231.

[18] Calhoun, C. A. (2003). Property valuation models and house price indexes for the provinces of Thailand: 1992-2000. Housing Finance International, 17(3), 31-41.

[19] Ćetković, J., Lakić, S., Lazarevska, M., Žarković, M., Vujošević, S., Cvijović, J., & Gogić, M. (2018). Assessment of the Real Estate Market Value in the European Market by Artificial Neural Networks Application. Complexity, 2018. doi:10.1155/2018/1472957.

[20] Fan, G. Z., Ong, S. E., & Koh, H. C. (2006). Determinants of house price: A decision tree approach. Urban Studies, 43(12), 2301–2316. doi:10.1080/00420980600990928.

[21] Gao, L., Guo, Z., Zhang, H., Xu, X., & Shen, H. T. (2017). Video Captioning with Attention-Based LSTM and Semantic Consistency. IEEE Transactions on Multimedia, 19(9), 2045–2055. doi:10.1109/TMM.2017.2729019.

[22] Demetriou, D. (2017). A spatially based artificial neural network mass valuation model for land consolidation. Environment and Planning B: Urban Analytics and City Science, 44(5), 864–883. doi:10.1177/0265813516652115.

[23] Park, B., & Bae, J. K. (2015). Using machine learning algorithms for housing price prediction: The case of Fairfax County, Virginia housing data. Expert Systems with Applications, 42(6), 2928–2934. doi:10.1016/j.eswa.2014.11.040.

[24] Ho, W. K. O., Tang, B. S., & Wong, S. W. (2021). Predicting property prices with machine learning algorithms. Journal of Property Research, 38(1), 48–70. doi:10.1080/09599916.2020.1832558.

[25] Mora-Garcia, R. T., Cespedes-Lopez, M. F., & Perez-Sanchez, V. R. (2022). Housing Price Prediction Using Machine Learning Algorithms in COVID-19 Times. Land, 11(11), 2100. doi:10.3390/land11112100.

[26] Jafary, P., Shojaei, D., Rajabifard, A., & Ngo, T. (2024). Automated land valuation models: A comparative study of four machine learning and deep learning methods based on a comprehensive range of influential factors. Cities, 151, 105115. doi:10.1016/j.cities.2024.105115.

[27] Gurmu, A., & Miri, M. P. (2023). Machine learning regression for estimating the cost range of building projects. Construction Innovation, 25(2), 577–593. doi:10.1108/CI-08-2022-0197.

[28] Sammour, F., Alkailani, H., Sweis, G. J., Sweis, R. J., Maaitah, W., & Alashkar, A. (2024). Forecasting demand in the residential construction industry using machine learning algorithms in Jordan. Construction Innovation, 24(5), 1228–1254. doi:10.1108/CI-10-2022-0279.

[29] Calainho, F. D., van de Minne, A. M., & Francke, M. K. (2024). A Machine Learning Approach to Price Indices: Applications in Commercial Real Estate. Journal of Real Estate Finance and Economics, 68(4), 624–653. doi:10.1007/s11146-022-09893-1.

[30] Jafary, P., Shojaei, D., Rajabifard, A., & Ngo, T. (2024). Automating property valuation at the macro scale of suburban level: A multi-step method based on spatial imputation techniques, machine learning and deep learning. Habitat International, 148, 103075. doi:10.1016/j.habitatint.2024.103075.

[31] Özalp, A. Y., & Akıncı, H. (2024). Comparison of tree-based machine learning algorithms in price prediction of residential real estate. Gümüşhane Üniversitesi Fen Bilimleri Dergisi, 14(1), 116-130.

[32] Mathotaarachchi, K. V., Hasan, R., & Mahmood, S. (2024). Advanced Machine Learning Techniques for Predictive Modeling of Property Prices. Information (Switzerland), 15(6), 295. doi:10.3390/info15060295.

[33] Hoxha, V. (2024). Comparative analysis of machine learning models in predicting housing prices: a case study of Prishtina's real estate market. International Journal of Housing Markets and Analysis, 18(3), 694-711. doi:10.1108/IJHMA-09-2023-0120.

[34] Gunes, T. (2023). Model agnostic interpretable machine learning for residential property valuation. Survey Review, 56(399), 525–540. doi:10.1080/00396265.2023.2293366.

[35] Areo, G. (2024). The Impact of Artificial Intelligence and Machine Learning on Real Estate: Current Applications and Future Trends. ResearchGate, 1-9.

[36] Su, T., Li, H., & An, Y. (2021). A BIM and machine learning integration framework for automated property valuation. Journal of Building Engineering, 44, 102636. doi:10.1016/j.jobe.2021.102636.

[37] Baur, K., Rosenfelder, M., & Lutz, B. (2023). Automated real estate valuation with machine learning models using property descriptions. Expert Systems with Applications, 213, 119147. doi:10.1016/j.eswa.2022.119147.

[38] Rafiei, M. H., & Adeli, H. (2016). A Novel Machine Learning Model for Estimation of Sale Prices of Real Estate Units. Journal of Construction Engineering and Management, 142(2), 4015066. doi:10.1061/(asce)co.1943-7862.0001047.

[39] Kim, G. H., Yoon, J. E., An, S. H., Cho, H. H., & Kang, K. I. (2004). Neural network model incorporating a genetic algorithm in estimating construction costs. Building and Environment, 39(11), 1333–1340. doi:10.1016/j.buildenv.2004.03.009.

[40] Gribniak, V., Mang, H. A., Kupliauskas, R., Kaklauskas, G., & Juozapaitis, A. (2016). Stochastic Tension-Stiffening Approach for the Solution of Serviceability Problems in Reinforced Concrete: Exploration of Predictive Capacity. Computer-Aided Civil and Infrastructure Engineering, 31(6), 416–431. doi:10.1111/mice.12183.

[41] El Hajj, B., Schoefs, F., Castanier, B., & Yeung, T. (2016). A Condition-Based Deterioration Model for the Stochastic Dependency of Corrosion Rate and Crack Propagation in Corroded Concrete Structures. Computer-Aided Civil and Infrastructure Engineering, 32(1), 18–33. doi:10.1111/mice.12208.

[42] Jang, Y., Jeong, I., & Cho, Y. K. (2021). Identifying impact of variables in deep learning models on bankruptcy prediction of construction contractors. Engineering, Construction and Architectural Management, 28(10), 3282–3298. doi:10.1108/ECAM-06-2020-0386.

[43] Elalem, Y. K., Maier, S., & Seifert, R. W. (2023). A machine learning-based framework for forecasting sales of new products with short life cycles using deep neural networks. International Journal of Forecasting, 39(4), 1874–1894. doi:10.1016/j.ijforecast.2022.09.005.

[44] Saha, P., Lyu, J., Desai, D., Chauhan, R., Jeyapaulraj, J., Chu, P., Sommer, P., & Mehta, D. (2024). Machine Learning-based Relative Valuation of Municipal Bonds. Proceedings of the 5th ACM International Conference on AI in Finance, 634–642. doi:10.1145/3677052.3698650.