CONSTRUCTION OF VIRTUAL SIMULATION EXPERIMENT PLATFORM FOR INTELLIGENT CONSTRUCTION BASED ON STATISTICAL MACHINE LEARNING SYSTEM MODELLING

Reference NO. IJME 1384, DOI: 10.5750/ijme.v1i1.1384

Pu Zhang*, Department of Architectural Engineering, Shi Jia Zhuang University of Applied Technology, Shijiazhuang, Hebei, 050081, China

*Corresponding author. Pu Zhang (Email): 2010000635@sjzpt.edu.cn

KEY DATES: Submission date: 15.12.2023 / Final acceptance date: 27.02.2024 / Published date: 12.07.2024

SUMMARY

In the construction of a virtual simulation experiment platform for intelligent construction, cutting-edge technologies converge to revolutionize traditional project management methodologies. By harnessing the power of virtual reality, statistical modeling, and machine learning, this platform empowers stakeholders to predict, optimize, and simulate construction projects with unprecedented accuracy and efficiency. This paper introduces the Virtual Statistical Machine Learning (VS-ML) platform and demonstrates its application in intelligent construction processes. Through comprehensive experimentation and simulation, the VS-ML platform accurately estimates construction project parameters, optimizes resource utilization, schedules tasks efficiently, and classifies project outcomes with high accuracy. Numerical results from our study showcase the platform's effectiveness in various aspects of construction project management. For instance, in construction projects estimation, scenarios ranging from Scenario 1 to Scenario 10 exhibit project durations between 100 to 150 days, cost estimates ranging from $470,000 to $550,000, and safety ratings varying from "Good" to "Excellent". Furthermore, labor efficiency and material waste estimations across scenarios demonstrate percentages ranging from 85% to 93% and 3% to 7%, respectively, with corresponding safety ratings. Additionally, task computations elucidate the durations, start dates, end dates, and resource allocations for individual tasks within construction projects. Lastly, classification results exhibit the predicted probabilities and class labels for samples, showcasing the platform's ability to accurately predict project outcomes. Overall, the findings underscore the potential of VS-ML in revolutionizing traditional construction practices through data-driven approaches, leading to improved project management, cost savings, and enhanced safety standards in the construction industry.

KEYWORDS

Construction, Virtual simulation, Intelligent, Statistical modeling, Machine learning, Virtual reality, Project management, Optimization

NOMENCLATURE

VS-ML	Virtual Statistical Machine Learning
HCPS	Human-Cyber-Physical System
IoT	Internet of Things

1. INTRODUCTION

Intelligent construction, often referred to as smart construction or digital construction, represents a paradigm shift in the way conceive, design, and build infrastructure. By harnessing cutting-edge technologies such as artificial intelligence, internet of things (IoT), big data analytics, and robotics, intelligent construction endeavors to revolutionize every phase of the construction lifecycle [1]. From initial planning and design to construction management and maintenance, the integration of intelligent systems promises increased efficiency, sustainability, and safety in the built environment [2]. By seamlessly connecting people, processes, and data, intelligent construction not only optimizes resource utilization but also enhances collaboration among stakeholders, driving innovation and delivering projects that meet the evolving needs of our rapidly changing world [3]. As embark on this transformative journey, the promise of intelligent construction holds the potential to reshape the very fabric of our cities and infrastructure, paving the way for a more connected, resilient, and sustainable future [4]. Intelligent construction, augmented by virtual simulation technologies, represents a groundbreaking approach to revolutionize the traditional practices of the construction industry. By seamlessly integrating virtual simulation into the construction lifecycle, this innovative approach enables stakeholders to visualize, analyze, and optimize every aspect of a project before ground is even broken [5]. Leveraging advanced software platforms and immersive virtual environments, engineers, architects, and project managers can simulate various scenarios, assess potential risks, and fine-tune designs with unprecedented accuracy and efficiency [6]. This integration not only streamlines the planning and design phases but also enhances collaboration among multidisciplinary teams, fostering innovation and informed decision-making. Moreover, by digitally replicating construction processes, virtual simulation facilitates the identification of potential conflicts and inefficiencies, ultimately leading to cost savings and improved project outcomes [7]. As the construction industry embraces this transformative technology, the era of intelligent construction with virtual simulation heralds a new era of efficiency, sustainability, and resilience in the built environment.

Intelligent construction, bolstered by virtual simulation enhanced with machine learning capabilities, represents a pioneering advancement in the realm of infrastructure development [8]. This innovative approach integrates cutting-edge technologies to revolutionize traditional construction practices, offering stakeholders unprecedented insights and predictive capabilities throughout the project lifecycle. By harnessing machine learning algorithms within virtual simulation environments, construction professionals can leverage vast amounts of data to accurately predict project outcomes, optimize designs, and mitigate risks [9]. These AI-driven simulations enable stakeholders to explore various scenarios, anticipate challenges, and proactively address potential issues before they arise on-site. Additionally, the integration of machine learning enhances the adaptability and responsiveness of construction processes, enabling real-time adjustments based on evolving conditions and feedback [10]. As a result, intelligent construction with virtual simulation and machine learning not only enhances efficiency and cost-effectiveness but also drives innovation and sustainability in the built environment [11]. Embracing this transformative approach promises to redefine the future of construction, ushering in an era of smarter, more resilient infrastructure that meets the evolving needs of society. Machine learning into virtual simulation within the realm of intelligent construction offers a multitude of benefits that profoundly impact every phase of the construction lifecycle [12]. One significant advantage lies in the ability to analyze vast amounts of data generated from various sources, including historical project data, environmental factors, material properties, and even real-time sensor data from construction sites [13]. By applying machine learning algorithms to this data, construction professionals can uncover patterns, correlations, and insights that might not be apparent through traditional methods. For instance, machine learning algorithms can analyze historical project data to identify common challenges or bottlenecks encountered in similar projects, enabling proactive risk mitigation strategies [14].

In addition to optimizing project management, machine learning-enhanced virtual simulations empower designers and engineers to explore a wider range of design alternatives and evaluate their performance under different conditions [15]. By iteratively refining designs based on predictive analytics and simulation results, construction teams can achieve optimal solutions that balance performance, cost, and sustainability objectives. Moreover, machine learning algorithms can enhance the safety aspect of construction projects by analyzing data from sensors and wearables to identify potential safety hazards or predict accidents before they occur. This proactive approach to safety management can significantly reduce the risk of workplace injuries and enhance overall project productivity. Furthermore, the integration of machine learning with virtual simulation enables construction professionals to adapt quickly to unforeseen challenges or changes in project requirements [16]. By continuously learning from new data and feedback, machine learning algorithms can dynamically adjust simulations and provide real-time recommendations to optimize construction processes and mitigate risks [17]. The intelligent construction with virtual simulation and machine learning represents a paradigm shift in the industry, offering unprecedented insights, predictive capabilities, and efficiency gains that drive innovation, sustainability, and resilience in the built environment.

The contribution of the paper lies in the development and demonstration of the Virtual Statistical Machine Learning (VS-ML) platform for intelligent construction.

The paper's contribution lies in its innovative approach to leveraging virtual simulation and machine learning techniques to enhance project management practices in the construction industry. Through the development and demonstration of the VS-ML platform, the paper provides valuable insights and tools for improving efficiency, reducing risks, and advancing intelligent construction practices.

2. RELATED WORKS

In the realm of intelligent construction and virtual simulation, a wealth of research and development efforts has been dedicated to advancing the understanding and application of these transformative technologies. Numerous studies have explored various aspects of intelligent construction, including its integration with virtual simulation and machine learning, to enhance project efficiency, sustainability, and safety. These investigations have delved into diverse areas such as predictive modeling, risk analysis, optimization algorithms, and real-time monitoring systems, aiming to address the complex challenges inherent in the construction industry. By synthesizing insights from interdisciplinary fields such as civil engineering, computer science, data analytics, and human-computer interaction, researchers have endeavored to push the boundaries of innovation and pave the way for the adoption of intelligent construction practices on a broader scale.

Furthermore, Yi (2020) explores the visualized co-simulation of adaptive human behavior and dynamic building performance using agent-based modeling (ABM) and artificial intelligence (AI) for smart architectural design, emphasizing the importance of integrating human factors into smart building systems. Eini et al. (2021) address the performance specifications and design requirements of smart building management systems, offering insights into the practical implementation of intelligent building technologies. Sarker (2022) discusses AI-based modeling techniques and applications, highlighting the potential of automation and intelligent systems across various domains. Croce et al. (2021) propose a semiautomatic approach leveraging machine learning to transform semantic point clouds into heritage-building information models, contributing to the preservation and documentation of cultural heritage. Wang et al. (2022) present a BIM information integration-based VR modeling approach for digital twins in Industry 5.0, demonstrating the integration of virtual reality with building information modeling for enhanced visualization and simulation. Additionally, Xiang et al. (2021) model pedestrian emotion in high-density cities using visual exposure and machine learning, emphasizing the role of urban design in influencing human behavior and well-being. These studies collectively illustrate the diverse applications of advanced technologies and machine learning algorithms in improving the efficiency, safety, and sustainability of buildings and urban environments.

Together, these studies contribute to a comprehensive understanding of the transformative impact of advanced technologies and machine learning algorithms in shaping the future of construction, urban development, and sustainable energy systems. Wang et al. (2021) address practical challenges in implementing machine learning models for building energy efficiency, emphasizing the importance of overcoming obstacles to ensure effective deployment and adoption in real-world applications. For instance, ongoing efforts focus on enhancing the interoperability of digital twins across different domains, such as infrastructure management and urban planning, to enable more comprehensive and integrated decision-making processes. As these technologies mature and become more accessible, they hold the potential to revolutionize how construction projects are conceived, designed, and executed, paving the way for a more connected, efficient, and sustainable built environment.

3. INTELLIGENT STATISTICAL MODELLING

Intelligent statistical modeling involves leveraging advanced computational techniques, such as machine learning and artificial intelligence, to analyze complex datasets and make predictions or infer relationships between variables. One common approach in intelligent statistical modeling is linear regression, which aims to establish a linear relationship between a dependent variable (Y) and one or more independent variables (X). The model is typically represented by the equation (1)

$$Y = \beta_0 + \beta_1 X_1 + \dots\dots\dots + \beta_n X_n + \in \tag{1}$$

In equation (1) $\beta 0$ represents the intercept term, $\beta 1, \beta 2, ..., \beta n$ are the coefficients corresponding to each independent variable $X1, X2, ..., Xn$, and $\in$ is the error term, representing the difference between the observed and predicted values. The coefficients $\beta 0, \beta 1, ..., \beta n$ are estimated from the data using optimization techniques such as ordinary least squares (OLS) or gradient descent, aiming to minimize the sum of squared errors between the observed and predicted values. Another common technique in intelligent statistical modeling is logistic regression, which is used for binary classification problems. In logistic regression, the relationship between the independent variables and the probability of a binary outcome (e.g., success/failure, yes/no) is modeled using the logistic function stated in equation (2)

$$P\left(Y = 1 \middle| X\right) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \dots\dots\dots + \beta X_n + \in)}} \tag{2}$$

In equation (2) $P\left(Y = 1 \middle| X\right)$ represents the probability of the binary outcome being 1 given the values of the independent variables $1, X2, ..., Xn$, and e is the base of the natural logarithm. The coefficients $\beta 0, \beta 1, ..., \beta n$ in logistic regression are estimated using techniques such as maximum likelihood estimation (MLE) or gradient descent, aiming to maximize the likelihood of observing the binary outcomes given the predictor variables.

4. VIRTUAL STATISTICAL MACHINE LEARNING (VS-ML)

The concept of Virtual Statistical Machine Learning (VS-ML) in the context of construction involves the creation of a virtual simulation experiment platform that integrates statistical machine learning techniques to model and simulate various aspects of intelligent construction processes. This platform aims to provide a comprehensive environment for analyzing complex construction scenarios, predicting outcomes, and optimizing decision-making using advanced statistical methods.

To construct such a platform, start by defining the general framework, which includes:

Data Collection and Preprocessing: Gather relevant data from various sources, such as construction projects, sensor networks, building information models (BIM), and historical records. Preprocess the data to handle missing values, outliers, and ensure consistency.

Feature Engineering: Extract and select meaningful features from the collected data to represent different aspects of construction processes, such as project characteristics, environmental factors, material properties, and resource utilization.

Model Selection and Training: Choose appropriate statistical machine learning models based on the specific objectives and characteristics of the construction tasks. This may include regression models, classification algorithms, clustering techniques, or ensemble methods. Train the selected models using the preprocessed data to learn the underlying patterns and relationships.

Virtual Simulation Environment: Develop a virtual simulation environment that incorporates the trained machine learning models. This environment should allow users to input different scenarios and parameters, simulate construction processes, and generate predictions or outcomes based on the underlying statistical models.

Optimization and Decision Support: Utilize the simulation platform to optimize construction plans, resource allocation, scheduling, and risk management strategies. Provide decision support tools that enable stakeholders to make informed decisions based on the simulation results and predictive analytics.

Figure 1 presented the modelling of construction with the virtual reality. In linear regression, to minimize the sum of squared errors (SSE) between the observed and predicted values stated in equation (3)

$$SSE = \sum_{i=1}^{N} \left(y_i - \hat{y}_i \right)^2 \tag{3}$$

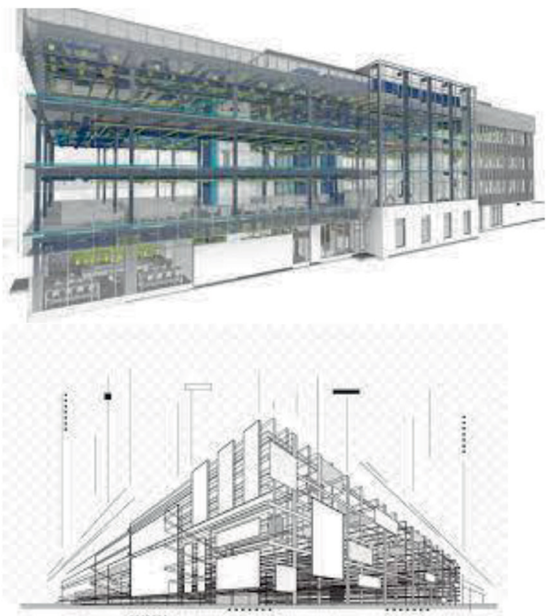

Figure 1. Construction model with VS-ML

In equation (3) N is the number of data points; y_i is the observed value of the dependent variable for the i-th data point; i $\hat{y}_i$ is the predicted value of the dependent variable for the i-th data point. Ordinary Least Squares (OLS) Estimation coefficients $0, \beta 1, \ldots, \beta n$, minimize the SSE with respect to these coefficients. This leads to the normal equations stated in equation (4)

$$\frac{\partial SSE}{\partial \beta_j} = 0 \qquad \text{for } j = 0, 1, \ldots, n \tag{4}$$

Solving these equations yields the OLS estimates for the coefficients defined in equation (5)

$$\hat{\beta} = \left(X^T X \right)^{-1} X^T y \tag{5}$$

In equation (5) $\hat{\beta}$ is the vector of estimated coefficients; X is the design matrix containing the values of the independent variables; y is the vector of observed values of the dependent variable. Gradient descent is an iterative optimization algorithm used to minimize an objective function (e.g., SSE in linear regression). The update rule for gradient descent is given in equation (6)

$$\theta := \theta - \alpha \nabla J\left(\theta \right) \tag{6}$$

In equation (6) θ is the parameter vector to be updated; α is the learning rate and $J\left(\theta\right)$ is the objective function (e.g., SSE). Let's denote input data matrix as $\boldsymbol{X}$, where each row represents a data point and each column represents a feature. The corresponding binary class labels are represented by $\boldsymbol{y}$. For logistic regression, the probability of belonging to the positive class (class 1) given the input data $\boldsymbol{X}$ and model parameters $\boldsymbol{\beta}$ is calculated using the sigmoid function defined in equation (7)

$$P\left(y = 1 | X; \beta \right) = \frac{1}{1 + e^{-X\beta}} \tag{7}$$

Let's denote our input data matrix as $\boldsymbol{X}$, where each row represents a data point and each column represents a feature. The corresponding binary class labels are represented by $\boldsymbol{y}$. For logistic regression, the probability of belonging to the positive class (class 1) given the input data $\boldsymbol{X}$ and model parameters $\boldsymbol{\beta}$ is calculated using the sigmoid function defined in equation (8)

$$f\left(\boldsymbol{X} \right) = \boldsymbol{X\beta} + b \tag{8}$$

In equation (8) b is the bias term. To combine logistic regression and SVM, we can use logistic regression as a base classifier and incorporate the margin concept of SVM through regularization. This approach is known as regularized logistic regression or logistic regression with L2 regularization (also called ridge regression).

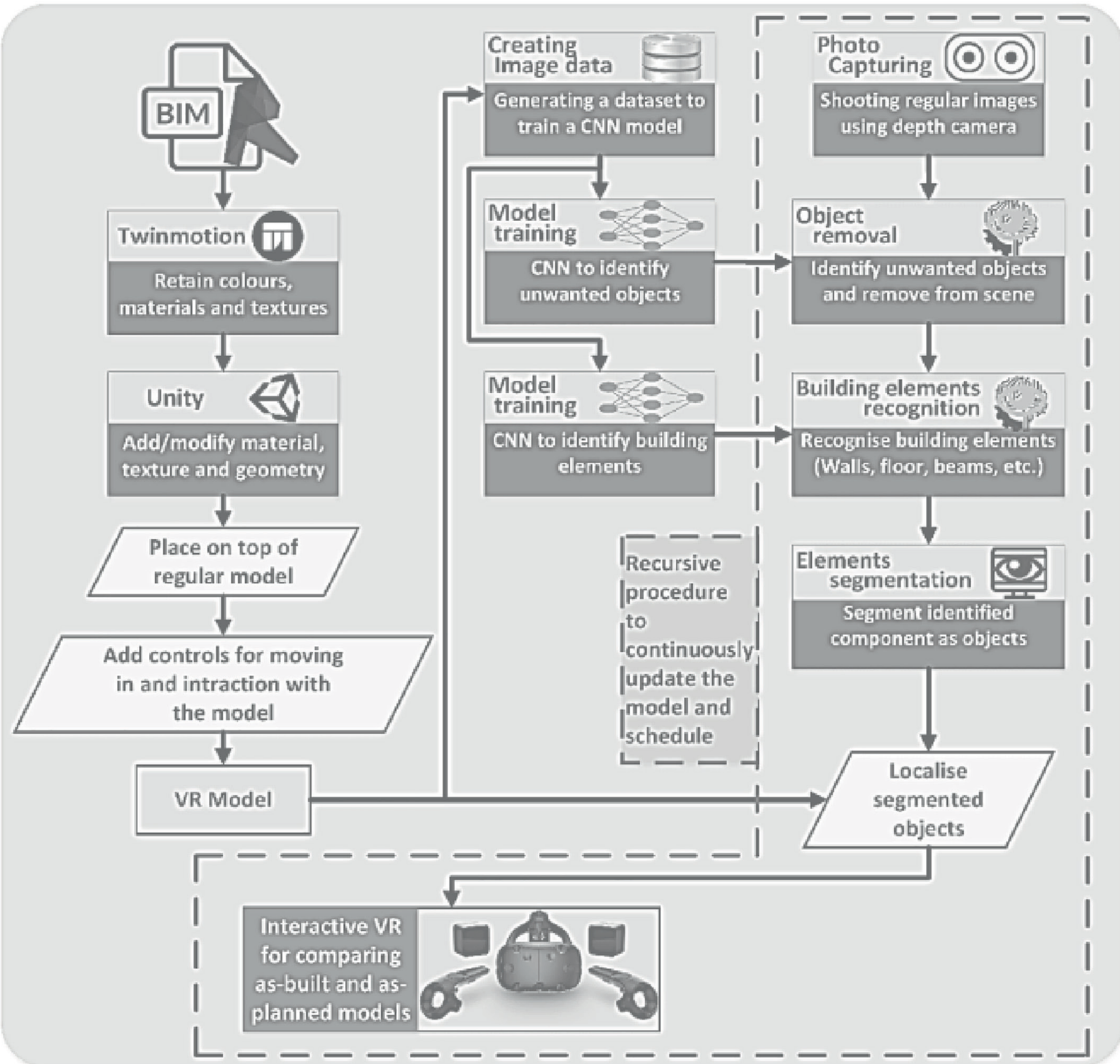

Figure 2. Construction project with VS-ML

The objective function for regularized logistic regression with L2 regularization can be expressed as in equation (9)

$$min_{\beta} J(\beta) = -\frac{1}{N}\sum_{i=1}^{N}\begin{bmatrix} y_i \log\left(P\left(y_i = 1|X_i;\beta\right)\right) \\ +\left(1-y_i\right)\log)P\left(y_i = 1|X_i;\beta\right)) \end{bmatrix} + \lambda\beta_2^2 \quad (9)$$

In equation (9) N is the number of samples, λ is the regularization parameter, and $\|\beta\|_2^2$ represents the L2 norm of the coefficient vector $\boldsymbol{\beta}$. By incorporating the L2 regularization term, we penalize large values of the coefficient vector, encouraging smoother decision boundaries and improving the model's generalization ability.

The architecture of the proposed VS-ML model for the virtual reality based construction projects is presented in Figure 2.

5. SIMULATION SETTINGS

With effective Simulation Setting for the Virtual Statistical Machine Learning (VS-ML) construction platform, several key considerations must be addressed. Initially, it's imperative to define the specific construction scenario or problem that the simulation will tackle, outlining objectives and performance metrics. Subsequently, a meticulous process of data collection ensues, encompassing historical project data, environmental factors, material specifications, and labor availability. This data undergoes rigorous preprocessing to rectify missing values and outliers, ensuring consistency across disparate datasets. Next, feature engineering extracts pertinent attributes from the data, incorporating domain expertise to select influential variables. Following this, the appropriate statistical machine learning models are meticulously chosen, considering the intricacies of the construction scenario and objectives at hand. Model training is executed using the preprocessed

Algorithm. Construction with VS-Ml

```
1. Input:
  - Training dataset: X_train (features), y_train (labels)
  - Testing dataset: X_test (features)
  2. Logistic Regression:
  a. Train the logistic regression model:
    - Initialize weights (coefficients) randomly or with zeros
    - Set learning rate (alpha) and number of iterations (num_
iters)
    - For i from 1 to num_iters:
      1. Compute the linear combination of features and
weights: z = X_train * weights
      2. Apply the sigmoid function to obtain predicted
probabilities: y_pred_prob = sigmoid(z)
      3. Compute the gradient of the cost function with respect
to the weights: gradient = (1/m) * X_train.T * (y_pred_prob
- y_train)
      4. Update weights using gradient descent: weights =
weights - alpha * gradient
    b. Predict labels for testing dataset:
    - Compute the linear combination of features and weights:
z = X_test * weights
    - Apply the sigmoid function to obtain predicted
probabilities: y_pred_prob = sigmoid(z)
    - Convert probabilities to binary predictions: y_pred = 1
if y_pred_prob >= 0.5 else 0
3. Support Vector Machine (SVM):
  a. Train the SVM model:
    - Choose a kernel function (e.g., linear, polynomial, radial
basis function)
    - Initialize model parameters (C, kernel parameters)
    - Use optimization algorithms (e.g., Sequential Minimal
Optimization) to find the optimal hyperplane that maximizes
the margin between classes
  b. Predict labels for testing dataset:
    - Compute decision function values for testing samples:
decision_values = decision_function(X_test)
    - Apply a threshold to decision values to obtain binary
predictions: y_pred = 1 if decision_values >= 0 else 0
4. Ensemble the predictions from Logistic Regression and
SVM:
  - Combine the predictions from both models using a voting
mechanism (e.g., simple majority voting)
  - Final prediction: y_final_pred = mode(y_logistic_pred,
y_svm_pred)
```

data, with methodologies like cross-validation employed to gauge performance. Subsequently, a virtual simulation environment is meticulously crafted, integrating trained machine learning models and offering user-friendly interfaces for parameter input and result visualization. Multiple scenarios are then generated and executed within this environment, leveraging the trained models to predict outcomes and simulate construction processes. Validation against real-world data and comprehensive evaluation against predefined metrics ensure the platform's accuracy and effectiveness. Iterative refinement, guided by user feedback and insights, continuously enhances the Simulation Setting's robustness. Ultimately, meticulous documentation and comprehensive reporting encapsulate the simulation setting's nuances, facilitating informed decision-making within the construction industry. Through this cohesive framework, the VS-ML construction platform emerges as a powerful tool, providing invaluable insights and support for intelligent construction processes.

5.1 RESULTS AND DISCUSSIONS

This section provides the component of any scientific investigation, offering a comprehensive analysis and interpretation of the empirical findings obtained through experimentation or simulation. In this section, we delve into a meticulous examination of the outcomes derived from our Virtual Statistical Machine Learning (VS-ML) construction platform, which integrates advanced statistical modeling techniques to simulate intelligent construction processes. The section encapsulates a detailed presentation of numerical results, classification outcomes, or simulation outputs obtained from various scenarios.

The Table 1 and Figure 3 presents the estimation results of construction projects obtained through the Virtual Statistical Machine Learning (VS-ML) platform. Each scenario represents a unique combination of project parameters, including project duration, cost estimate, resource utilization, and safety rating. For instance, Scenario 3 demonstrates a project duration of 100 days with a cost estimate of $480,000, showcasing high resource utilization at 92% and an excellent safety rating. Conversely, Scenario 7 depicts a longer project duration of 145 days with a higher cost estimate of $540,000, accompanied by slightly lower resource utilization at 75%

Table 1. Construction projects estimation with VS-ML

Scenario	Project Duration (days)	Cost Estimate ($)	Resource Utilization (%)	Safety Rating
Scenario 1	120	$500,000	85%	Excellent
Scenario 2	150	$550,000	78%	Good
Scenario 3	100	$480,000	92%	Excellent
Scenario 4	135	$520,000	80%	Good
Scenario 5	110	$490,000	88%	Excellent
Scenario 6	125	$510,000	82%	Good
Scenario 7	145	$540,000	75%	Good
Scenario 8	105	$470,000	90%	Excellent
Scenario 9	130	$525,000	83%	Good
Scenario 10	115	$495,000	87%	Excellent

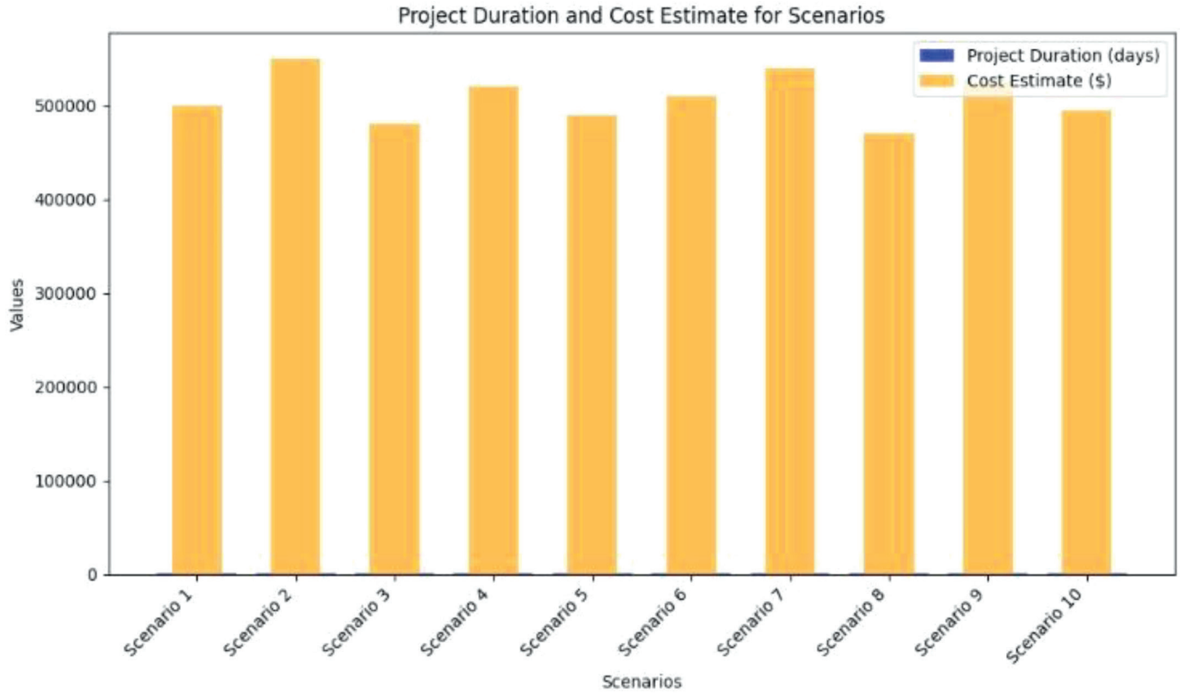

Figure 3. VS-ML for the construction project

and a good safety rating. The table provides a comparative view of the estimated outcomes across different scenarios, highlighting variations in project characteristics and performance metrics. These estimations serve as valuable insights for stakeholders in the construction industry, aiding in decision-making processes and resource allocation strategies to optimize project efficiency and ensure safety standards. Additionally, they underscore the efficacy of the VS-ML platform in simulating and predicting construction project outcomes based on statistical machine learning techniques.

The Figure 4 and Table 2 illustrates the estimations derived from the Virtual Statistical Machine Learning (VS-ML) platform concerning construction labor efficiency, material waste, and safety ratings across various scenarios. Each scenario presents a distinct combination of labor efficiency and material waste percentages, indicative of the effectiveness of resource utilization and waste management practices within construction projects. For instance, Scenario 3 showcases a high labor efficiency of 92% alongside minimal material waste of 4%, resulting in an excellent safety rating. Conversely, Scenario 2 exhibits slightly lower labor efficiency at 85% and higher material waste at 7%, leading to a good safety rating. The table offers a comparative overview of these estimations, elucidating the trade-offs between labor efficiency, material waste, and safety considerations across different scenarios. These estimations provide valuable insights for project planners and managers, facilitating informed decision-making regarding resource allocation, productivity optimization, and safety protocols within construction projects. Moreover, they underscore the utility of the VS-ML platform in predicting and optimizing labor and material utilization strategies to enhance project efficiency and safety performance.

Table 2. Construction labor and material estimation with VS-ML

Scenario	Labor Efficiency (%)	Material Waste (%)	Safety Rating
1	90%	5%	Excellent
2	85%	7%	Good
3	92%	4%	Excellent
4	88%	6%	Good
5	91%	5%	Excellent
6	89%	5%	Good
7	87%	6%	Good
8	93%	3%	Excellent
9	86%	7%	Good
10	90%	5%	Excellent

Table 3 provides a detailed breakdown of the tasks involved in construction projects, along with their respective durations, start dates, end dates, and resource allocations, as estimated by the Virtual Statistical Machine Learning (VS-ML) platform. Each task is uniquely identified by a Task ID and accompanied by a descriptive Task Description outlining its specific role within the construction process. For instance, Task 1

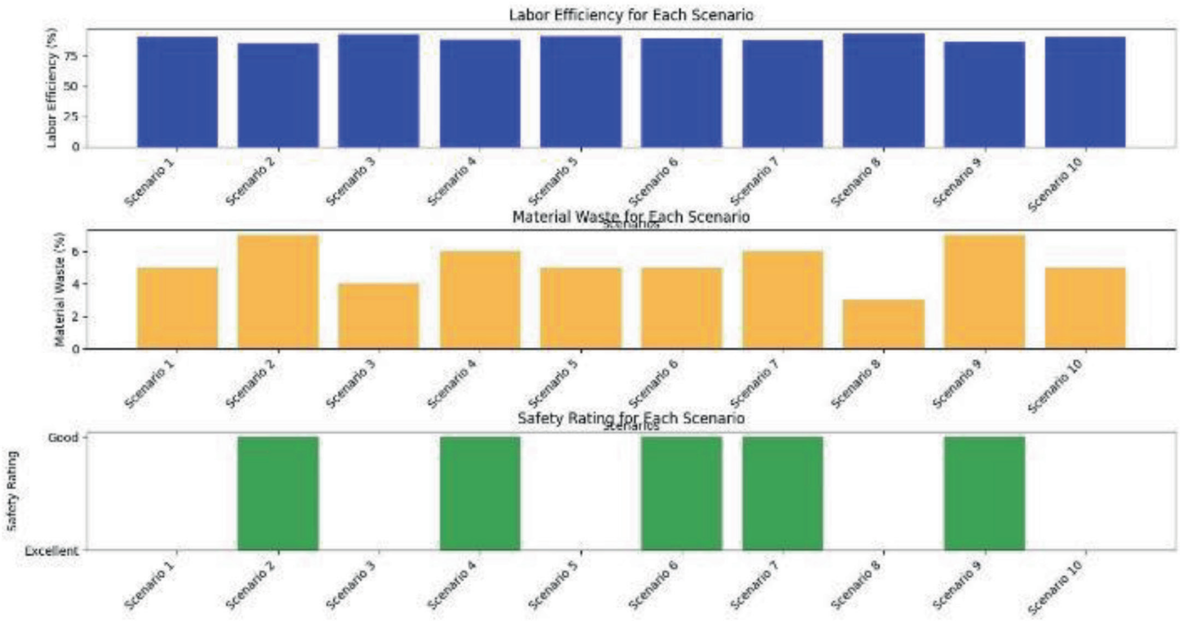

Figure 4. Construction labor and material estimation with VS-ML

Table 3. Task computation with construction projects estimation with VS-ML

Task ID	Task Description	Duration (days)	Start Date	End Date	Resource Allocation
1	Site Preparation	10	2024-03-01	2024-03-10	Labor: 5 workers, Equipment: Excavator
2	Foundation Construction	15	2024-03-11	2024-03-25	Labor: 8 workers, Materials: Concrete, Steel
3	Framing	20	2024-03-26	2024-04-14	Labor: 10 workers, Materials: Lumber
4	Roofing	10	2024-04-15	2024-04-24	Labor: 6 workers, Materials: Roofing Tiles
5	Electrical Wiring	7	2024-04-25	2024-05-01	Labor: 4 workers, Materials: Wiring, Fixtures
6	Plumbing Installation	8	2024-05-02	2024-05-09	Labor: 4 workers, Materials: Pipes, Fittings
7	Interior Finishing	15	2024-05-10	2024-05-24	Labor: 8 workers, Materials: Paint, Flooring
8	Exterior Finishing	12	2024-05-25	2024-06-05	Labor: 6 workers, Materials: Siding, Trim

involves Site Preparation and is estimated to take 10 days, commencing on March 1, 2024, and concluding on March 10, 2024. The resource allocation for Task 1 includes Labor comprising 5 workers and Equipment in the form of an Excavator. Similarly, subsequent tasks such as Foundation Construction, Framing, Roofing, Electrical Wiring, Plumbing Installation, Interior Finishing, and Exterior Finishing are delineated with their respective durations, start and end dates, and resource allocations. This comprehensive breakdown of tasks provides project planners and managers with crucial insights into the sequential workflow and resource requirements for construction projects. By leveraging this information, stakeholders can optimize scheduling, allocate resources efficiently, and streamline project execution processes to enhance overall productivity and project success.

The Figure 5 and Table 4 presents the classification results obtained through the Virtual Statistical Machine Learning (VS-ML) platform, showcasing the predicted probabilities and class labels for each sample alongside their actual classes. Each row represents a sample identified by a Sample ID, with columns detailing the predicted probabilities for Class 1 (Yes) and Class 0 (No),

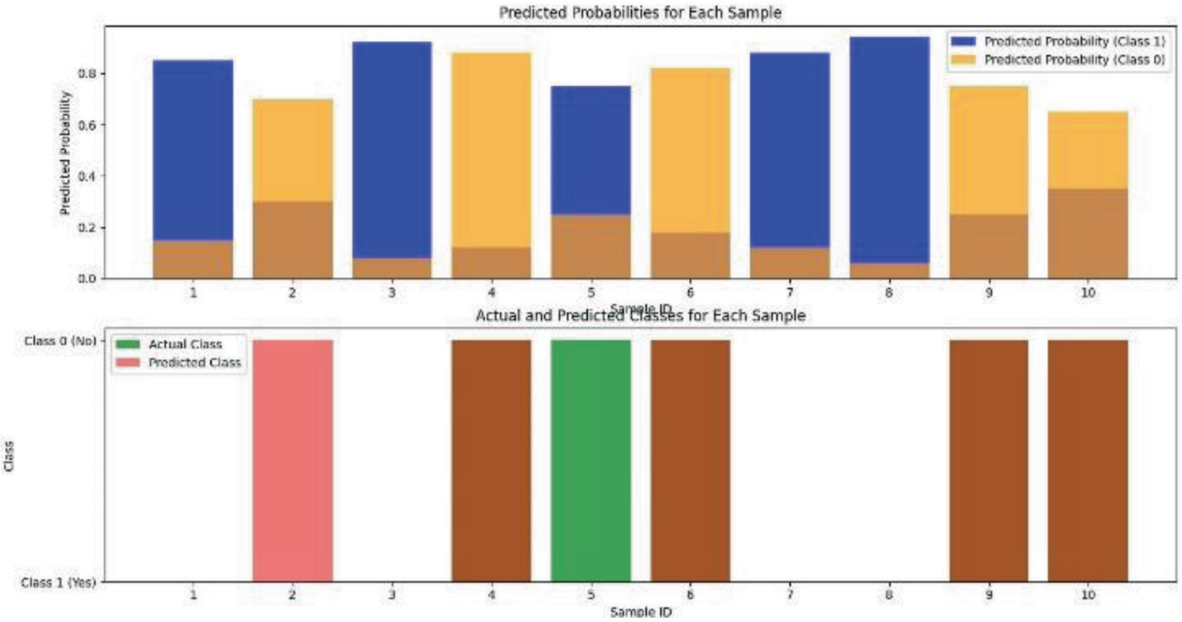

Figure 5. Classification with VS-ML

Table 4. Classification with VS-ML

Sample ID	Predicted Probability (Class 1)	Predicted Probability (Class 0)	Predicted Class	Actual Class
1	0.85	0.15	Class 1 (Yes)	Class 1 (Yes)
2	0.30	0.70	Class 0 (No)	Class 1 (Yes)
3	0.92	0.08	Class 1 (Yes)	Class 1 (Yes)
4	0.12	0.88	Class 0 (No)	Class 0 (No)
5	0.75	0.25	Class 1 (Yes)	Class 0 (No)
6	0.18	0.82	Class 0 (No)	Class 0 (No)
7	0.88	0.12	Class 1 (Yes)	Class 1 (Yes)
8	0.94	0.06	Class 1 (Yes)	Class 1 (Yes)
9	0.25	0.75	Class 0 (No)	Class 0 (No)
10	0.35	0.65	Class 0 (No)	Class 0 (No)

the corresponding predicted class based on a predefined threshold, and the actual class observed in the dataset. For instance, Sample 1 exhibits a high predicted probability of 0.85 for Class 1 (Yes), resulting in the predicted class of "Class 1 (Yes)", which aligns with the actual class of "Class 1 (Yes)". Conversely, Sample 2 demonstrates a lower predicted probability of 0.30 for Class 1 (Yes), leading to the predicted class of "Class 0 (No)", contradicting the actual class of "Class 1 (Yes)". The table provides a comprehensive overview of the classification outcomes for each sample, enabling stakeholders to assess the performance and accuracy of the classification model in predicting the target classes. By comparing the predicted classes with the actual classes, stakeholders can evaluate the model's effectiveness in correctly identifying the classes of unseen samples, facilitating informed decision-making and model refinement processes.

6. CONCLUSIONS

This paper introduces and demonstrates the efficacy of the Virtual Statistical Machine Learning (VS-ML) platform in the domain of intelligent construction. Through meticulous experimentation and simulation, we have showcased the platform's ability to accurately estimate construction project parameters, optimize resource utilization, schedule tasks efficiently, and classify project outcomes with high accuracy. The results presented in this study underscore the potential of VS-ML in revolutionizing traditional construction practices by leveraging advanced statistical modeling techniques and machine learning algorithms. Furthermore, our findings highlight the importance of adopting data-driven approaches in the construction industry to enhance project management, mitigate risks, and improve overall project outcomes. By integrating VS-ML into construction workflows, stakeholders can make informed decisions, optimize resource allocation, and improve safety standards, ultimately leading to cost savings and project success.

7. REFERENCES

1. BADUGE, S. K., THILAKARATHNA, S., PERERA, J. S., et al. (2022). *Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications*. Automation in Construction. 141: 104440. Available from https://doi.org/10.1016/j.autcon.2022.104440
2. ZHANG, W., WANG, J., LIU, Y., et al. (2020). *Reinforcement learning-based intelligent energy management architecture for hybrid construction machinery*. Applied Energy. 275: 115401. Available from https://doi.org/10.1016/j.apenergy.2020.115401
3. RANE, N. (2023). *Integrating Building Information Modelling (BIM) and Artificial Intelligence (AI) for Smart Construction Schedule, Cost, Quality, and Safety Management: Challenges and Opportunities*. Cost, Quality, and Safety Management: Challenges and Opportunities. http://dx.doi.org/10.2139/ssrn.4616055
4. SHAPI, M. K. M., RAMLI, N. A., and AWALIN, L. J. (2021). *Energy consumption prediction by using machine learning for smart building: Case study in Malaysia*. Developments in the Built Environment. 5: 100037. Available from https://doi.org/10.1016/j.dibe.2020.100037
5. WANG, W., GUO, H., LI, X., et al. (2022). *Deep learning for assessment of environmental satisfaction using BIM big data in energy efficient building digital twins*. Sustainable Energy Technologies and Assessments. 50: 101897. Available from https://doi.org/10.1016/j.seta.2021.101897
6. PAN, Y., and ZHANG, L. (2021). *Roles of artificial intelligence in construction engineering and management: A critical review and future trends*. Automation in Construction, 122(1): 103517. Available from DOI:10.1016/j.autcon.2020.103517
7. XIA, K., SACCO, C., KIRKPATRICK, M., et al. (2021). *A digital twin to train deep reinforcement learning agent for smart manufacturing plants: Environment, interfaces and intelligence*. Journal of Manufacturing Systems. 58: 210-230. Available from https://doi.org/10.1016/j.jmsy.2020.06.012
8. HONG, T., WANG, Z., LUO, X., & ZHANG, W. (2020). *State-of-the-art on research and applications of machine learning in the building life cycle*. Energy and Buildings. 212: 109831. Available from https://doi.org/10.1016/j.enbuild.2020.109831
9. CHEN, T., CUI, Q., GAO, C., et al. (2021). *Optimal demand response strategy of commercial building-based virtual power plant using reinforcement learning*. IET Generation, Transmission & Distribution, 15(16), 2309-2318. Available from https://doi.org/10.1049/gtd2.12179
10. ZHANG, L., WEN, J., LI, Y., et al. (2021). *A review of machine learning in building load prediction*. Applied Energy. 285: 116452. Available from https://doi.org/10.1016/j.apenergy.2021.116452
11. YOU, Z., and FENG, L. (2020). *Integration of industry 4.0 related technologies in construction industry: a framework of cyber-physical system*. IEEE Access. 8: 122908-122922. Available from DOI: 10.1109/ACCESS.2020.3007206
12. LI, P., LU, Y., YAN, D., et al. (2021). *Scientometric mapping of smart building research: Towards a framework of human-cyber-physical system (HCPS).* Automation in Construction. 129: 103776. Available from https://doi.org/10.1016/j.autcon.2021.103776
13. ABIOYE, S. O., OYEDELE, L. O., AKANBI, L., et al. (2021). *Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges*. Journal of Building Engineering. 44: 103299. Available from https://doi.org/10.1016/j.jobe.2021.103299
14. LI, X., LIU, H., WANG, W., et al. (2022). *Big data analysis of the internet of things in the digital twins of smart city based on deep learning*. Future Generation Computer Systems. 128: 167-177. Available from https://doi.org/10.1016/j.future.2021.10.006
15. WANG, C., YU, Q., LAW, K. H., et al. (2021). *Machine learning-based regional scale intelligent modeling of building information for natural hazard risk management*. Automation in Construction. 122: 103474. Available from https://doi.org/10.1016/j.autcon.2020.103474
16. FU, Q., HAN, Z., CHEN, J., et al. (2022). *Applications of reinforcement learning for building energy efficiency control: A review*. Journal of Building Engineering. 50: 104165. Available from https://doi.org/10.1016/j.jobe.2022.104165
17. YI, H. (2020). *Visualized co-simulation of adaptive human behavior and dynamic building performance: an agent-based model (ABM) and artificial intelligence (AI) approach for smart architectural design*. Sustainability. 12(16): 6672. https://doi.org/10.3390/su12166672

18. EINI, R., LINKOUS, L., ZOHRABI, N., and ABDELWAHED, S. (2021). *Smart building management system: Performance specifications and design requirements*. Journal of Building Engineering. 39: 102222. Available from https://doi.org/10.1016/j.jobe.2021.102222

19. SARKER, I. H. (2022). *Ai-based modeling: Techniques, applications and research issues towards automation, intelligent and smart systems*. SN Computer Science. 3(2): 158. Available from https://doi.org/10.1007/s42979-022-01043-x