Multi-Stage Classification of Construction Site Modeling Objects Using Artificial Intelligence Based on BIM Technology

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Abstract — **Background: AI, IoT, and BIM technologies are revolutionizing the building business. This study applies these methods to the multi-stage categorization of construction site modeling items to create an "evolutionary" digital twin.**

Objective: Develop and test a BIM-AI method integrating CNN and FFNN architectures. The goals are BIM project identification, classification, and assessment throughout their life cycle.

Methods: The approach uses moving cameras for picture modeling and IoT integration. Augmented reality and big data technologies explore the dynamic transformation of actual building structures into BIM representations. An AI system that analyzes construction site modeling items using CNN and FFNN is a major part of the study.

Results: The article highlights the usefulness of site conformity detection during BIM model building, displaying consistency and quantifying ongoing operations. The study shows that scaling point cloud and mesh models and optimizing the "evolutionary" BIM project of the building site's digital twin are promising.

Conclusion: The findings of this study provide important insights and improve BIM modeling techniques, notably in creating a multi-stage "evolutionary" digital twin of the building site. This pioneering construction site modeling using BIM and AI opens the door to future developments and improvements.

I. Introduction

Nowadays, BIM technologies have attained an extraordinary level of integration with many new technologies, such as artificial intelligence, the Internet of Things (IoT), Big Data, and Augmented Reality (AR), which has significantly increased the quality and speed of the entire set of operations and processes related to construction project modeling, implementation, and support. The generation of digital twins of the BOM and the construction site, in general, was an essential branch of the direction.

The purpose of this research is to provide scientific support for the concepts of multi-stage modelling of building site objects utilizing artificial intelligence based on BIM technology. The author's team created a concept that defines the BOM creation process in the BIM system as being separated into an arbitrary number of pieces on a suitable timetable. Such changes enable the formation of a model with distinct evolutionary development and growth dynamics. The implementation of a Structure from Motion (SfM) system, which will allow the creation of digital models from photographs from the construction site and displays a three-dimensional depiction of the state of the BOM in real-time, is critical to the collection of training and learning data. This technology will enable neural networks to categorize not only one representation of a BOM picture, but three reciprocal representations at the same time, namely point clouds, mesh models, and the BOM itself. These will enable the YOLOv5 and FFNN artificial intelligence models to identify faults more precisely during the execution of the BOM on the construction site.

The study conducted by Deng, Menassa, and Kamat [1] sheds light on the revolutionary convergence of construction Information modelling (BIM) and Bill of Materials (BOM) in construction site modelling. They place BIM at the forefront of the AEC-FM sector's digital revolution by closely monitoring the development of intelligent building representations via comprehensive research. This introduction aims to explore the diverse capabilities of BIM by analysing the contributions of Mengiste, de Souza, and Hartmann [2], who integrated image-based appearance data into BIM, and Hosseini and Maghrebi, who utilised 4D-BIM to handle complex construction site risks. These developments enhance our comprehension of Building Information Modelling capabilities and provide the groundwork for a more advanced and unified method of modelling building sites. This article seeks to analyse the capacity of AI-driven BIM methodologies to improve the accuracy, efficiency, and comprehensiveness of multi-stage modelling operations carried out on construction sites.

Three researchers from the University of Michigan, M. Deng, C. Menassa, and V. Kamat, conducted a rigorous theoretical investigation of the development of BIM technologies across time. According to the paper [1], BIM technologies have evolved in five stages, as shown below:

1. Level 1. Static 3D BIM visualization tool;
2. Level 2. BIM model analyses and simulations;
3. Level 3. BIM and IoT method integration;
4. Level 4. BIM and artificial intelligence methods integration;
5. Level 5. Make a digital twin.

It is vital to highlight that in order to accomplish the fifth level, all preceding levels must be implemented in a single BIM project.

II. Literature Review

In scientific publications [2-4] the authors consider SfM systems when resolving problems by building three-dimensional models from a point cloud using photometry or videometry. Scientists list a wide variety of uses for SfM systems, such as simulating worker evacuation from a construction site to visualize the site's actual condition, reducing variance between planned and actual conditions, and creating an "as-built" model of an object based on an image of it for reconstruction. Also defined is the ability to interact with images taken by SfM in real-time and by BIM standards. Geometric information is extracted using three-dimensional grid models utilizing tools such as Meshroom (AliceVision 2020), Agisoft Photoscan, or COLMAP [5].

In the collection of scientific studies [6-8]scientists take intelligent technologies, including SfM [9], into consideration and find that when scaling projects, they frequently lead to Big Data, which in turn necessitates the use of advanced management, diagnostics, and forecasting from the executors and visualization of this data, in particular, using modern capabilities of The idea of big data analysis is also given a lot of attention since it makes it possible to address several issues linked to the productivity and digitization of different spheres of human activity. As a result, machine learning, intelligent data analysis techniques, and a variety of statistics have all been included in big data analytics.

In papers [10, 11], researchers examine BIM building employing IoT analysis. In addition, the authors determine the considerable importance of high-tech cloud solutions in connecting to the IoT. Given the expansion of BIM technology, it is expedient and important to use IoT, which is defined as a combination of physical and virtual components such as sensors, mechanisms, cloud services, communications, and protocols, to create digital twins of BOM and construction sites. This serves as the foundation for IoT systems.

In the article [12], a team of scientists from Istanbul Technical University - G. Sezen, M. Cakir, M. E. Atik, and Z. Duran - conduct an experimental study where they investigate precision, recall and mean average precision (mAP) are used as evaluation metrics among YOLOv3, YOLOv4, YOLOv5, and Faster R-CNN algorithms [13]. Thus, based on the results of model training and direct tests, it was concluded that model YOLOv5 [14, 15] is the fastest and most productive when compared to YOLOv4 and others.

Researchers from the Kyiv National University of Construction and Architecture, S. Dolhopolov, T. Honcharenko, S. A. Dolhopolova, O. Riabchun, M. Delembovskyi, and O. Omelianenko, worked to define the multi-label classification process. The study [16] provided a practical example of how to employ multi-label classification with FFNN [17, 18] to address issues with a sizable number of input and output classes and the potential to scale into Big Data problems. The design of FFNN is impacted by the duties assigned to the performers, according to the findings of scientific research. To illustrate the parameter space, for instance, training on several parameters is necessary when doing a regression on multiple parameters.

The goal of this study is to provide an analytical foundation for an information system that will allow the concept of multi-stage modeling of building site objects using artificial intelligence based on BIM technology to be confirmed. Achieving this goal may result in the development of a quality standard for working with homogeneous BOMs, which will be decided by the intricate interaction of IoT, Big Data, BIM, YOLOv5, SfM, and FFNN [4].

III. Methodology

Considering a complete examination of the scientific works of scientists of various profiles and proving the concept of multi-stage modeling of construction site objects using artificial intelligence based on BIM technology. Fig. 1 shows the developed model of an information system that allows you to study a construction object or construction site in real-time and highlight aspects that allow you to model the representation of a construction object in a three-dimensional projection using SfM and IoT cameras. As a result, point clouds, mesh models, and BOMs with varied levels of detail are modeled [19]. In the architecture of YOLOv5, each model of a building object is described as a class, allowing artificial intelligence to identify many photographs based on the stages of execution of the object on the construction site. The categorization data is then sent to the FFNN, which is compared to the standardized data that the project customer expects. As a result, the system's last procedure is to give the user information about the compliance of a certain building object with the standards, which can be determined manually or based on the pre-formed Dataset BOM. The unique feature of this information system's operation is the ability to determine whether the derived models of the architectural item reflect its general trends.

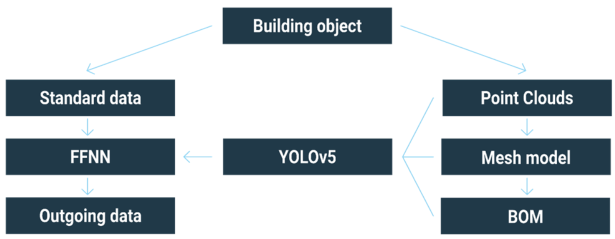

Fig. 1. Multi-stage modeling of building site items in an information system model

The process of obtaining information, known as photo modeling or videometry, is carried out via IoT devices, which can be used in two ways. Fig. 2 shows static photo modeling, which is distinguished by the fact that cameras are installed just once and are utilized throughout the whole observation process, and dynamic photo modeling, which may not require the installation of as many cameras and is in motion at specific time intervals.

The advantages of the first method are complete autonomy and reliability of the data collection procedure. However, in the case of a big-scale construction project, a large amount of equipment may be necessary, which is why, in some circumstances, dynamic photo modeling is preferable, especially if building operations are slow [20, 21].

Thus, within the framework of the study, we have the opportunity to extract information from panoramic photos or photo sequences and model on their basis Point Clouds [22], Mesh models [23], and BOMs [24] of varying degrees of detail based on the project requirements using photo modeling and SfM, which is based on the Agisoft Photoscan software. Geometric forms are replicated with varying degrees of detail during photo modeling (approximately one point for every 5 cm of real size) [25-27]. The higher the image quality, the more detail is captured and the more natural it appears. In practice, however, different sets of input photos are frequently required. Fig. 3 shows the BOM construction process utilizing photo modeling and SfM.

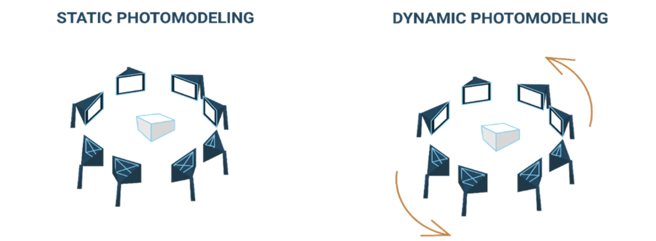

Fig. 2. Possibilities for implementing photo modeling of the modeled building object

Within the scope of the project, 600 visualizations of BOM construction fragments were performed at various time intervals and construction objects, forming the study's learning and training Dataset[27]. Fig. 4 shows one of the BOM construction fragments on a real-world example of a building object with serial №5.

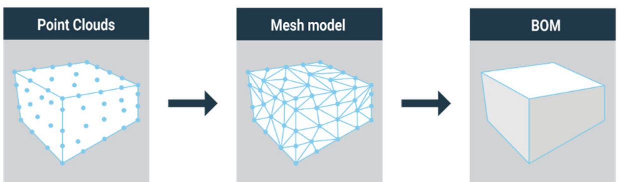

Fig. 3. The BOM building process employs photo modeling and SfM

A dataset of 600 complete images of the building object was created as part of the study's framework (i.e., 2400 images representing the building object, Point Clouds, BOM, and Mesh Model). The artificial intelligence system recognizes diverse construction sites and their resulting models before determining their resemblance and compliance with the defined standard [28, 29]. Following the development of the models, they were manually tagged for additional training. Given the YOLOv5 [30] model's excellent performance as the fastest and most successful model in the YOLO [31] family, it was chosen for the categorization of building items and their derived models. Experiment results showed that 100 iterations of training took no more than 8 minutes of real-time.

The evaluation metrics chosen were Average Precision – the average accuracy for a given class, and Mean Average Precision (mAP) [32]– the average accuracy for all classes.

The value of the average precision of the Point Clouds model is determined by equation:

$$AP_{PC} = \frac{\sum_{i=1}^{n} x_i}{n} = \frac{x_1 + x + x_3 + \cdots + x_n}{n}, \tag{1}$$

where AP_{PC} is Average Precision for Point Clouds model;

x_i is Average Precision for each iteration of the building object according to the Point Clouds model.

The value of the average precision of the Mesh model is determined by equation:

$$AP_{MM} = \frac{\sum_{i=1}^{n} y_i}{n} = \frac{y_1 + y_2 + y_3 + \cdots + y_n}{n}, \tag{2}$$

where AP_{MM} is Average Precision for Mesh model; y_i is Average Precision for each iteration of the building object according to the Mesh model.

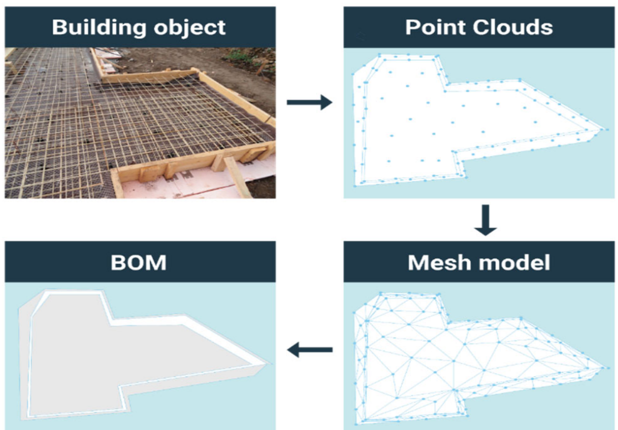

Fig. 4. BOM construction using photo modeling and SfM for sample №5

The value of the average precision of the BOM is determined by equation:

$$AP_{BOM} = \frac{\sum_{i=1}^{n} \omega_i}{n} = \frac{\omega_1 + \omega_2 + \omega_3 + \cdots + \omega_n}{n}, \tag{3}$$

where AP_{BOM} is Average Precision for BOM; ω_i is Average Precision for each iteration of the building object according to the BOM.

The value of the average precision of the class is determined by equation:

$$AP = \frac{AP_{PC} + AP_{MM} + AP_{BOM}}{3}, \quad (4)$$

where AP is general Average Precision of the class; AP_{PC} is Average Precision for Point Clouds model; AP_{MM} is Average Precision for Mesh model; AP_{BOM} is Average Precision for BOM.

The value of the mean average precision (mAP) is determined by equation:

$$mAP = \frac{\sum_{j=1}^{k} AP_i}{k}, \quad (5)$$

where AP_i is Average Precision of i-class; mAP is mean Average Precision; k is number of defined classes to recognize.

Fig. 5 shows the visualization of mathematical processes depicted in (1), (2), (3), (4), and (5) during YOLOv5 work on creating object classification.

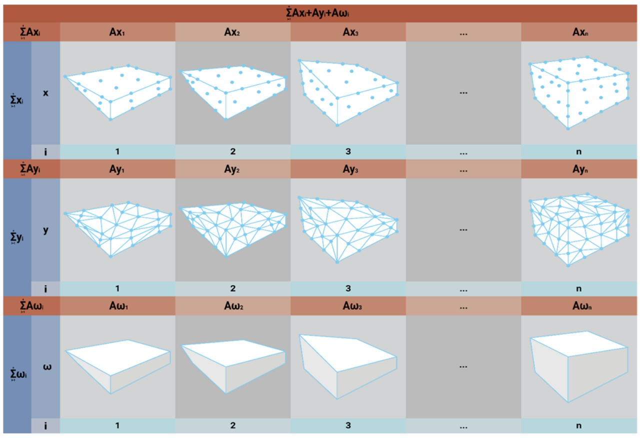

Fig. 5. Visualization of mathematical processes about the derivatives of the building object during their classification

The following libraries and software were used in the study: Python 3.8, Numpy, Keras, Tensorflow, Pytorch, json, pandas, CUDA 11.1, and OpenCV 3.2.0.

The YOLOv5 model is trained in the ratio of 80% of training images, and 20% of test images. Images were separated according to the stages of development of simple building things. Table I shows the training parameters for the YOLOv5 model.

TABLE I. THE TRAINING PARAMETERS TO MODEL YOLOV5

Parameter	Value
Epochs	500
Image size	416
Batch size	16
Training time	42 min

Comparison according to the FFNN model should be performed when certain standards are defined. The artificial limits that the standard must take into account are shown in Table II.

TABLE II. LIMITATION TO THE INSTANCE OF CLASS №5 RELATIVE TO THE FFNN MODEL

	APBO	APPC	APMM	APBOM
Value	0.9	0.9	0.9	0.9

IV. RESULTS

Metrics were computed for all classes defined in the Dataset. The maximum Average Precision for the general classification was found for specimen №5 and was 0.88. In general, the YOLOv5 model produced correct classification results for the stated classes and had no discrepancies. However, because some building objects were more difficult to distinguish, the mAP of the YOLOv5 model is 0.73. Fig. 6 shows an example of the findings of Instance №5. BO5, BOPC5, BOM5, and BOMM5 are building object, building object (Point Cloud model), building object model (BOM), and building object (Mesh model) in this example, respectively.

Table III shows the generalized YOLOv5 classification results by building objects. The indicators range from 0 to 1 and are pre-normalized.

TABLE III. YOLOV5 MODEL CLASSIFICATION RESULTS

Name of the class	APBO	APPC	APMM	APBOM	AP	mAP
BO1	0.79	0.73	0.72	0.79	0.76	0.73
BO5	0.93	0.83	0.85	0.91	0.88	
BO10	0.69	0.61	0.59	0.69	0.65	
BO15	0.86	0.77	0.69	0.81	0.78	
BO25	0.91	0.8	0.77	0.77	0.81	
BO40	0.81	0.68	0.6	0.79	0.72	
BO60	0.69	0.59	0.59	0.6	0.62	

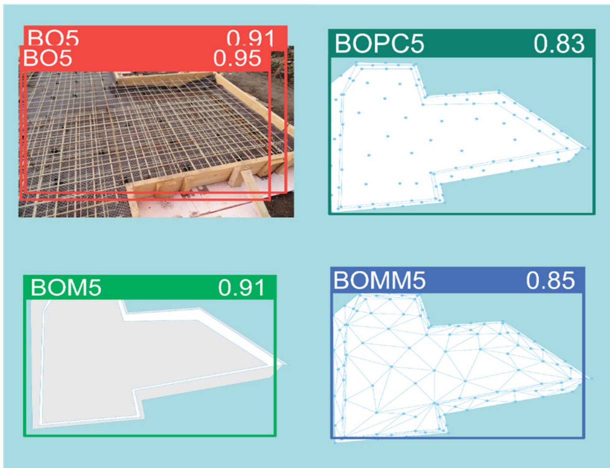

Fig. 6. BOM construction is based on photo modeling and SfM classification results based on building objects. The indicators are pro-normalized and range from 0 to 1

Table IV shows how the FFNN model works regarding the standards given by the customer based on the building objects. The indicators range from 0 to 1 and are pre-normalized. As a result, the acquired values demonstrate the conformity of classified architectural objects and their derivative models to the required requirements.

TABLE IV. THE FFNN MODEL'S COMPARISON RESULTS FOR THE INSTANCE OF CLASS №5

	Resulting APRO	Resulting APPC	Resulting APMM	Resulting APBOM	Resulting AP
Value	1.0	0.92	0.94	1.0	0.98

V. DISCUSSION

Combining AI with Building Information Modelling (BIM) in the construction industry has significantly enhanced project management, site safety, and overall construction efficiency. This study contributes to the expanding knowledge base in the field by using artificial intelligence to categorise objects used in construction site modelling via a multi-stage procedure. This approach could enhance the accuracy and efficiency of site management.

The findings of Deng et al. align with our results since they examined the progression of IBRs and emphasised the transition from building information modelling (BIM) to digital twins [33]. The step-by-step approach is crucial for constructing the multi-stage item categorisation of site modelling as it provides a more precise and comprehensive representation of the locations. Integrating AI into this process extends beyond the mere advancement of technology; it entails its use in pragmatic, day-to-day scenarios.

In their study, Hosseini and Maghrebi examined the use of 4D-BIM (four-dimensional building information modelling) and AI (artificial intelligence) for fire emergency evacuation on complex construction sites [34]. Our approach aligns with theirs in addressing site safety, a crucial aspect of the construction process. Similarly, our work enhances on-site safety protocols using artificial intelligence to assess and manage potential hazards.

Our ARTICLE also examines the integration of image-based data into BIM, a topic investigated by Mengiste et al. [2]. We have shown the practical value of this integration via AI algorithms to evaluate visual data and enhance item classification on the construction site.

Kaiser et al. proposed the co-registration of video-grammetric point clouds with BIM, showcasing the ability of AI to align visual data with BIM models [4] accurately. By incorporating AI into the categorisation process, our research enhances and broadens the concept, offering a more comprehensive depiction of the construction site and its components.

In addition to integrating BIM, AI has several applications in the construction business. Sezen et al. used deep learning techniques to automate the detection of specific construction segments [12], which aligns with our findings. We have enhanced operational efficiency by significantly minimising the need for human involvement via automating the categorisation process.

Honcharenko et al. demonstrated the use of BIM and AI in the construction design and planning phases [21]. Their analysis centred on AI-powered modelling tools used in urban planning. Our research has shown that building site components may be precisely depicted and later classified when they are included in the planning phase.

Furthermore, Akselrod et al. [34] emphasise that digital firms relying on BIM should include AI throughout all building project stages. Our solution exemplifies the transformative potential of AI and BIM in the construction sector by ensuring continuous classification and monitoring of items used in building site models.

The article contributes to the expanding literature on artificial intelligence in the construction industry, aligning with contemporary academic patterns. Integrating artificial intelligence and building information modelling technologies into the multi-stage categorisation of objects on construction sites has created new possibilities for enhancing project management and optimising construction processes. Further progress in AI is expected to expand its use in the construction sector, providing more opportunities for improving efficiency and safety.

VI. CONCLUSION

The article introduces an innovative methodology for construction site modeling and the categorization of objects. The study showcases the practicability of using artificial intelligence and construction Information Modeling (BIM) technology to conduct multi-stage modeling of construction site elements. The study results highlight the potential advantages of this novel technique.

The primary accomplishment of the study is the effective categorization of things found at construction sites using temporal intervals. An information system was implemented to facilitate the categorization process, which is an essential component in the oversight and administration of building projects. Artificial intelligence, namely the YOLOv5 model, has shown notable efficacy in this endeavor. The YOLOv5 model demonstrated efficient learning capabilities, completing 500 iterations in 92 minutes. Furthermore, it attained a commendable mean Average Precision (mAP) score of 0.73. It implies that implementing AI-based time interval categorization has significant potential as a beneficial instrument for monitoring building progress and facilitating scheduling.

The YOLOv5 model has expanded its functionalities to include the classification of construction items based on their class and derivative models such as Point Cloud, Mensh model, and Bill of Materials (BOM). Using a multi-faceted categorization technique facilitates a complete comprehension of the many elements and phases involved in building projects. Using artificial intelligence (AI) to discern and classify these aspects can optimize project management and enhance the process of decision-making.

The article makes a noteworthy addition by examining quality criteria using the Feedforward Neural Network (FFNN) model. The FFNN model was used to analyze generic indications based on class in the study. However, the findings indicate that the model has the potential to be tailored to specific stages of a construction object's evolution. The adaptability in evaluating quality conforms to the ever-changing characteristics of construction projects, whereby criteria and demands may fluctuate throughout the project's lifespan. The examination of models and standards demonstrated a notable level of compliance, underscoring the precision of the information system model.

Furthermore, the study presents two separate methodologies for establishing the construction site for photogrammetric modeling: static and dynamic. This decision offers a range of options for data gathering techniques, enabling construction experts to choose the most appropriate solution according to the specific demands and limitations of the project.

The ramifications of this study transcend the confines of academia. The study results have significant practical implications, especially in Augmented Reality (AR) technology. Using the insights acquired via the multi-stage categorization of BIM-based building items allows for using augmented reality (AR) to improve the visualization and presentation of Bill of Materials (BOMs) throughout different project phases. The use of this technology has promise for enhancing communication, facilitating decision-making processes, and enabling more effective project monitoring within the construction sector. Incorporating this project into cloud storage to manage large volumes of data may significantly improve the efficiency of project execution. Cloud-based solutions provide significant advantages in the context of large-scale building projects. These advantages include scalability, accessibility, and real-time collaboration options.

The study provides a comprehensive analysis of using artificial intelligence and building information modeling technology in multi-stage categorization, shedding light on the dynamic changes occurring within the construction sector. The effective amalgamation of artificial intelligence models, information systems, and quality standards exemplifies the capacity to augment project management and decision-making procedures. Moreover, the potential of using Augmented Reality and cloud storage offers promising opportunities for future advancements and innovation within the construction industry.

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