Kalpa Publications in Computing
Volume 22, 2025, Pages 1–15
Proceedings of The Sixth International Conference on Civil and Building Engineering Informatics

Heterogeneous Graph Neural Networks-based Paper Drawings Automatic Layering Method

Xun Lu[1] and Yantao Yu[1,2*]
[1] Department of Civil and Environmental Engineering, The Hong Kong University of Science and Technology, Hong Kong 999077, China
[2] HKUST Shenzhen-Hong Kong Collaborative Innovation Research Institute, Shenzhen 518045, China
xun.lu@connect.ust.hk, ceyantao@ust.hk

Abstract

Building Information Modelling (BIM) can significantly improve aging buildings' smart operation and maintenance (O&M) efficiency, and support advanced equipment maintenance and emergency response. However, many aging buildings lack BIM due to the era in which they were built, and the manual reconstruction process requires experts with specialized knowledge and consumes considerable modeling time. Many existing studies utilize deep learning methods based on image features to extract component information from paper drawings for BIM reconstruction, however, the paper drawing layering pre-processing, which is essential for improving the information extraction accuracy, still requires inefficient manual drafting and line classification. Although existing studies have proposed methods for drawings layering by line classification, these methods perform poorly on construction engineering drawings due to the complexity and line dense in drawings. To fill this gap, we propose a heterogeneous graph neural networks (GNNs) based method that predicts the category of line elements on paper drawings to achieve automatic layering with three modules: 1) paper drawing vectorization by line extraction and duplicate elements merging to detect the line elements representing component contour and annotation; 2) graph structure construction by considering the different topological relationships among lines to represent the line properties; 3) heterogeneous graph nodal classification model to predict the line category and realize automatic layering. The proposed method was tested on an actual engineering drawing dataset, and the results show that the method has an overall F1 score more than 0.74 and exceeds the baseline model by over 0.1. This research improves paper drawing pre-processing efficiency and provides a new solution for information extraction in ageing buildings BIM reconstruction.

* Corresponding author

1 Introduction

Building information model (BIM) integrates building structural architectural and facility management data from diverse data sources and it is the foundation of and information of building smart operation (Hu et al., 2022). Many existing studies apply BIM to energy retrofit (Kamel & Memari, 2019), emergency response (Feng et al., 2021) and facility management (Hu et al., 2016), etc., which shows BIM's great potential to improve ageing building O&M efficiency and reduce cost. Despite it benefits, the ageing buildings built more than 20-30 years ago often lack BIM due to the technology limitations, and the manual BIM reconstruction process is knowledge- and labor-intensive (de Wilde, 2019), because it requires experts with specific knowledge to collect building information from original building documents. To improve ageing building's BIM reconstruction efficiency, the automatic information extraction and BIM reconstruction methods are required.

Building drawings contain accurate geometric and semantic information about building components (Yin et al., 2020). For ageing building BIM reconstruction, paper drawings are an ideal data source, because they are stored throughout the ageing building's life cycle as part of the deliverables of building completion. What's more, paper drawings have lower acquisition costs and there are no data privacy issues caused by on-site data collection processes. Many existing studies have been devoted to extracting information from raster drawings obtained by scanning or photocopying paper drawings for BIM reconstruction (Pan et al., 2023). Since different components are represented on the same plan by discrete pixels, some factors such as occlusion and overlapping between components will affect the accuracy of information extraction. It is necessary to divide building components of different categories and sizes into layers, thereby improving BIM reconstruction performance (Pan et al., 2023; Zhao et al., 2021). However, the layering pre-processing requires converting paper drawings into vector drawings (such as CAD drawings) by manual drafting, which is low efficient. Considering that most ageing buildings typically lack vectorized format drawings, there is an urgent need for an effective method to layer paper drawings according to component categories automatically.

Line elements represent most of the building component contour and annotations. Substantial research (Fan et al., 2021; Kim et al., 2021; Xie et al., 2022) has been conducted to classify line elements categories on drawings. Some studies focus on the classification of lines on the Piping and instrument diagram (P&ID) (Kim et al., 2021), where the line element category can be analyzed by the attached specific symbols. However, these methods do not adopt to construction drawings because component shapes are represented by proportional contours rather than abstract symbols. And the image features-based Convolutional Neural Networks (CNNs) methods cannot be directly used to predict pixel categories due to lack of texture. Other studies map the line elements in mechanical drawings to homogeneous graph structures where the line elements are represented by nodes, the edges represent adjacent relationships between lines, and Graph neural networks (GNNs) models are used to predict line categories. The GNN-based methods do not suffer from feature sparse issues. However, the line density in construction drawings exceeds that in mechanical drawings. The topological relationship of lines in a drawing cannot be expressed solely in terms of adjacency. It should consider the heterogeneous relationships among lines. Moreover, except for the line geometric attributes, the distribution of nearby texts is also the basis for determining the line category. Therefore, there is still room for improvement in the line classification of construction paper drawings.

Considering these limitations, this study proposes a paper drawings line elements vectorization and layering method to automate the ageing building paper drawings automatic layering process of BIM reconstruction. For improving the paper drawing layering efficiency, this study 1) automates the drawing line elements vectorization process through image processing; and 2) accurately classifies line elements by a heterogeneous GNN-based nodal classification method. This study will provide the ageing building BIM reconstruction field with a new information extraction method, which will help enhance the ageing building O&M efficiency.

2 Literature Review

This section reviews information extraction methods for BIM reconstruction based on paper drawings to demonstrate the motivation for this study. Moreover, this section introduces related line classification and layering methods, these methods are not adaptable for ageing building paper drawing layering due to the difference in research object or scope of application of these methods. Based on the review, the research gaps are identified.

2.1 BIM Reconstruction Information Extraction Method Based on Paper Drawings

Building drawings can be divided into CAD vector drawings, raster drawings, and paper drawings. CAD drawings store drawing elements in vectorized format, which can provide accurate geometric information of building components and the standardized layer name can also provide semantic information such as component categories (Yin et al., 2020). However, due to technological development, many ageing buildings can only obtain hand-drawn or paper drawings from existing completion documents. These paper drawings are generally converted to raster format through electronic scanning or photography for data storage and transmission. The information extracted from drawings for BIM reconstruction mainly includes geometric and semantic information. Geometric information typically refers to the components' locations, shapes, and the drawing coordinate system (Pan et al., 2023); semantic information typically refers to components' categories (Xu et al., 2024) or other drawing elements' categories (such as symbols and tags (Moon et al., 2021; Pan et al., 2023)).

Existing research uses various deep learning-based methods to extract geometric information and semantic information from drawings, because these methods are more robust to different drawing scales or rotations. For deep learning-based methods, drawing layering pre-processing is the necessary step to improve information extraction accuracy. Regarding geometric information extraction, the overlapping and obscuration of different categories of lines will affect the geometric information extraction performance. Since the instance masks generated by instance segmentation methods usually has a rough outline which cannot be directly used for BIM reconstruction, some studies combine instance segmentation results with image processing methods, such as connected domain algorithm (Pan et al., 2023), to simultaneously extract the accurate geometric contour and component category. Drawing layering is necessary for these methods because the overlapped line elements can segment complete contour and lead to incomplete contour detection results. Regarding semantic information extraction, many components on drawings have a similar appearance (for example, many components are represented by similar geometric primitives such as rectangles or polygons), which will mislead the deep learning model (Zhao et al., 2021). Therefore, drawing layering can improve the semantic information extraction performance. Moreover, drawing layering can enrich the intuitive representation of semantic data in paper drawings, such as component categories, etc., and enhance the computer's perception and understanding of drawings (Lin et al., 2023), thus supporting more complex BIM reconstruction tasks.

In summary, paper drawings are important information sources for ageing building BIM reconstruction. Automatic information extraction from drawings through deep learning methods can improve modeling efficiency. Although drawing layering is the key to improving geometric and semantic information extraction accuracy, few studies have focused on this issue. Motivated by the current research status, this study aims to propose an automatic paper drawing layering method, including drawing vectorization and line classification.

2.2 Automatic Line Classification and Layering Method

The objective of paper drawing layering is to identify drawing elements that represent different components and export them to different layers. In construction engineering drawings, line elements represent most building components and annotation information, extensive drawing layering research focuses on drawing line classification. Line classification methods can be divided into conventional methods and deep learning methods. Similar to drawing information extraction, conventional methods such as template matching (Kang et al., 2019) or heuristic rule-based detection (Moreno-García et al., 2017) have problems of poor adaptability and poor generalization to drawing rotation and scale changes respectively. As for those machine learning-based methods, the feature types used for classification mainly include visual features and graph features.

The visual feature-based methods employ CNNs to extract pixel-scale drawing visual features. Based on these features, object detection or instance segmentation methods classify individual pixels that makeup drawing line elements, and pixel areas of the same classification are marked as component contours. However, line classification methods based on visual features perform poorly due to the pixel sparsity and lack of texture of line elements (Fan et al., 2021; Xie et al., 2022). Some relevant studies combine drawing symbol detection and line extraction to predict the line types through heuristic matching rules (Kim et al., 2021; Moon et al., 2021). This kind of method, however, only adapts to the drawings representing information by lots of abstract symbols and lines, such as P&ID. In construction engineering drawings, in addition to the axis and annotation lines, other line elements generally represent the actual location and contour of the component. Therefore, when classifying component line elements such as wall contours, the symbol detection-based methods are not adaptable.

The GNN constructs graph structure according to the message-passing mechanism between the graph nodes and generate the embedding vectors that represent the node attribute and connection relationship with neighbors for the downstream classification tasks. Compared with visual features, the GNN-based methods are not affected by similar appearance. Existing studies encode the position, size, and other attributes of line elements into nodal features, and constructs edges between nodes according to the adjacent relationship to construct a homogeneous graph structure (Xie et al., 2022; W. Zhang et al., 2023), then the GNN model is used to conduct line classification on mechanical drawings, which achieved good results. However, the density of lines in construction engineering drawings is greater, and adjacent contour lines and annotation lines often have similar attributes, making it hard to predict the categories solely by relying on the geometric attributes of lines. Moreover, in engineering practice, human engineers often refer to the lines' nearby annotation texts to understand drawings. Therefore, it is necessary to consider the impact of the semantic information of the annotation text when conducting line classification tasks. Regarding the relationship between line elements, in addition to the adjacency relationship, construction engineering drawings also include many parallel lines (such as wall contours represented by parallel lines). However, current homogeneous graph-based line classification research fails to consider this relationship. Heterogeneous graph is a type of graph structure that encompasses multiple types of nodes and edges, which can represent more complex data systems with different relationships. Therefore, this study aims to propose a heterogeneous graph structure to represent the complex line relationships of construction engineering drawings.

In summary, the GNN-based method can encounter the challenge of sparse visual features compared to the CNN-based methods, but existing GNN-based research failed to accurately classify dense and complex line elements in construction engineering drawings. As a result, this study designs a type of heterogeneous graph structure to accurately represent the complex engineering drawings. The line elements in the drawings are treated as graph nodes, and the line location, size attributes, as well as information of nearby annotation texts are encoded as nodal features. And the graph edges are used to represent the adjacency and parallel relationships between lines.

2.3 Research Gaps

It is observed that most paper drawing layering methods 1) only consider the geometric attributes of line elements and fail to simultaneously encode the annotation text information as node features, and 2) are unable to encompass complex topological relationships between line elements. As a result, the line elements in ageing building paper drawings cannot be accurately classified, affecting the paper layering pre-processing and information extraction accuracy for BIM reconstruction.

3 Methods

The proposed paper drawings' automatic layering method is shown in Figure 1. Given a paper drawing as input, the drawing vectorization module will automate the drawing vectorization process by extracting line elements. Specifically, the line thinning processing will be conducted to reduce subsequent line duplication detection due to different line widths, then the LSD line detection method (Grompone von Gioi et al., 2010) will extract the vectorized format line elements by detecting line endpoints. In the graph construction module, a nodal feature list is proposed to consider the line geometric attributes and their relationship with adjacent annotation texts, and two types of edges, including adjacent and parallel edges are constructed according to the topological relationship with adjacent line elements. This graph construction strategy can accurately represent the characteristics of line elements by considering line attributes and surrounding texts simultaneously, and represent more complex relationships among line elements in construction engineering drawings. In the GraphSAGE (Graph SAmple and aggreGatE) (Hamilton et al., 2017)-based line classification module, a GraphSAGE model architecture suitable for the heterogeneous graph structures proposed in this study is developed. The GraphSAGE model is an inductive representation learning method that is not limited to fixed graph structure, which enables the line classification model learned from training set drawings to generalize to different drawings. The following sections detail each module.

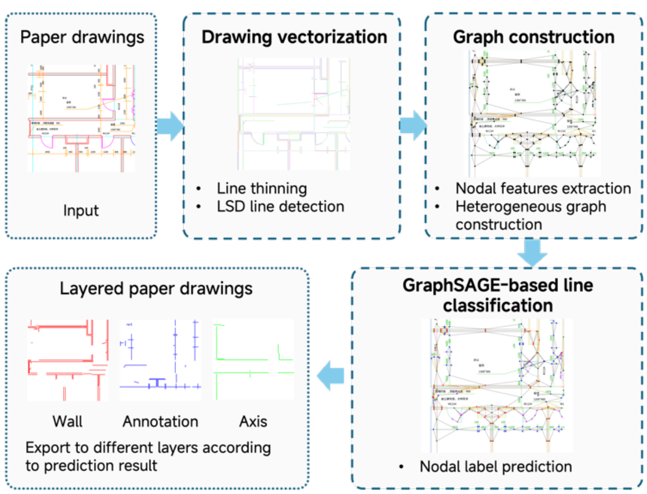
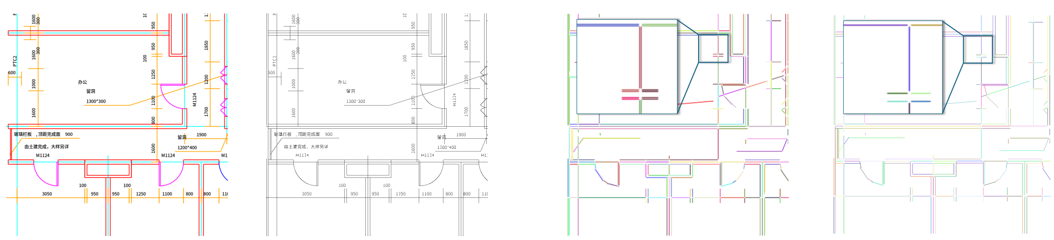


Figure 1. The roadmap of the proposed method

3.1 Drawing Vectorization

The purpose of drawing vectorization is to convert line elements from a combination of discrete pixels to vectorized elements represented by endpoints, which are used to construct the graph structure. Given that different categories of drawing elements typically have different line thicknesses, for example, contour lines of walls are usually wider than annotation lines, which will cause different distance between line pairs in the next line extraction step. Therefore, the line thinning step is necessary. This study employs line thinning algorithm proposed by Zhang and Suen (T. Y. Zhang & Suen, 1984) to get the skeletons of line elements, the input drawing and result of line thinning is shown in Figure 2 (a) and (b) separately.

Based on the line element skeletons, the vectorized line elements are obtained through line detection. In this step, LSD line detection method is utilized due to its superior adaptation to high-resolution raster drawings compared with Hough transform method, which is commonly used in other studies (Kim et al., 2021; Moon et al., 2023). The LSD detector generates parallel lines on both sides of original line elements. To ensure that parallel lines belonging to the same original elements are correctly paired, a line grouping algorithm is devised in this study. This algorithm assesses the parallelism of current lines, pairing those of similar length and within a specified threshold distance. The formed line pairs are shown in Figure 2 (c) with each line pair represented by a distinct color. Note that the prior line thinning ensures uniform thickness across all original line elements, facilitating the establishment of distance thresholds for pairing. Finally, to get the line vectors represent original line elements, two lines in a line pair are merged by averaging the endpoint coordinates. The result of drawing vectorization is shown in Figure 2 (d). The drawing vectorization module automates the manual drafting involved in paper-based BIM reconstruction and generates vectorized line elements for graph construction in the subsequent phase.



(a) Input paper drawing (b) Result of line thinning (c) LSD line detection (d) Line pairs merging

Figure 2. Drawing vectorization processing

3.2 Graph Construction

The heterogeneous graph structure plays an important role in embedding the line attributes and contextual topological relationships. In the proposed graph structure, nodes correspond to line elements extracted in the vectorization processing, while edges represent the adjacent and parallel relationship within line elements.

This study introduces a nodal feature list to encode the line element's geometric attributes and the relationship with nearby annotation texts. As illustrated in

Table 1, the features include the position, dimension, angle and relationship with texts of each line elements. Specifically, the coordinates and lengths of the line endpoints are normalized to the dimensions of the drawings (in this study, the dimension of raster format paper drawings is 1000 *

1000) to ensure that the position and dimension features remain invariant across varying drawing sizes. The angle feature is the angle with horizontal direction. Regarding the textual relationships, the annotation text type distinguishes between numeric and non-numeric content. Text type encoding is crucial as numeric text typically signifies dimensions, whereas non-numeric text commonly denotes component categories, axis labels, room types, and so on. The text direction feature indicates whether the text aligns with the line horizontally. The purpose of encoding text direction is that text describing a line typically has the same orientation as the line. Furthermore, both vertical and extended text directions are encoded to comprehensively capture the topological relationships with neighboring texts. In each direction, the text features include five elements, representing the presence of text, the proportion of numeric to non-numeric text, and the ratio of parallel numeric and non-numeric text lines.

Table 1. Nodal features for encoding line element attributes

Feature type	Description	Feature dimension
Position	2D coordinate of line endpoints	4
Dimension	Length	1
Angle	Angle with horizontal direction in drawing	1
Relationship with texts	Proportion of different types and directions of annotation text within the vertical direction neighbor of line elements	5
	Proportion of different types and directions of annotation text within the extended direction neighbor of line elements	5

The proposed heterogeneous graph incorporates two different kind of edges that represent adjacent and parallel relationship between line elements separately. The adjacent edges are generated from the connected or intersecting line elements, capturing the combination relationship of contour lines or intersection between component contours and annotation lines. The parallel edges are generated from the nearby parallel lines within a specified threshold distance. Parallelism holds significant relevance in construction engineering drawings, evident in features like walls delineated by parallel lines and dimension lines indicating component sizes and scales. The introduction of parallel edges aims to depict the praralleI relationships among line elements, enabling a more t detailed representation of complex drawings. In summary, the graph structure can be defined as:

$$G(N,\ E_a,\ E_p),\ N \in \mathbb{R}^{n_N \times 16},\ E_a \in \mathbb{Z}^{n_{E_a} \times 2},\ E_p \in \mathbb{Z}^{n_{E_p} \times 2} \tag{2}$$

where N represents the nodal features of the constructed graph, with n_N denoting the number of nodes which is also the number of line elements in drawing. E_a denotes the edge indices of undirected adjacent edges, with n_{E_a} indicating the quantity of adjacent edges. E_p represents the edge indices of undirected parallel edges, with n_{E_p} representing the number of parallel edges. The line element category, as well as the nodal label is defined as $Y \in \mathbb{Z}^{n_N}$. In this study, the line element category is separated as wall lines, annotation lines, axis lines and other lines. The method for constructing ground truth labels is partially adapted from (W. Zhang et al., 2023). As shown in Figure 3, in original vectorized format drawings, each category is specified with a unique color. The extracted line elements are redrawn to the original drawings (as depicted by black pixels in Figure 3), then the ground truth label is determined by counting the number of pixels of corresponding color in redrawn range.

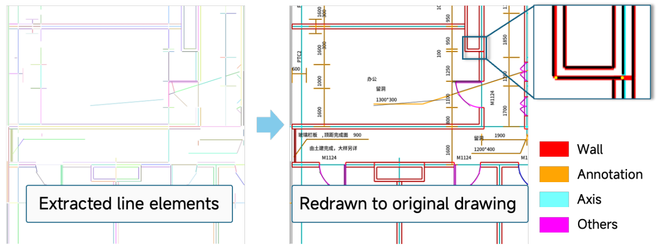
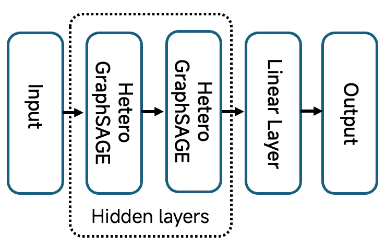


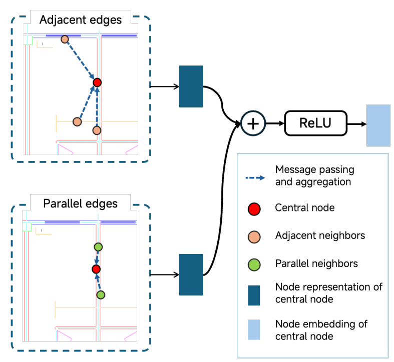
Figure 3. Extracted line elements ground truth label obtaining process

3.3 GraphSAGE-based Line Classification

Based on the constructed graph structure, the line classification task transformed into a nodal classification task. This study introduces a GraphSAGE-based model to tackle nodal classification. GraphSAGE is a superior nodal classification model, which allows the training of an embedding function to aggregate nodal features from local neighborhood. The embedding function can be generalized to unseen graphs (such as drawings in the validation set) without requiring additional training, thereby enhancing the applicability and adaptability of the line classification method. Figure 4 (a) shows the structure of the proposed GraphSAGE-based model, the node embeddings of the input graph are generated through two heterogeneous GraphSAGE layers. These node embeddings are then transformed into one-dimension vector through linear layers to represent classification result. The structure of each hidden layer is depicted in Figure 4 (b), showcasing a hetero-GraphSAGE layer structure is proposed to aggregate information from adjacent neighbors and parallel neighbors of central node. For each type of edge, the hetero-GraphSAGE layer samples neighbor nodes attribute features to generate messages, which are then aggregated with the central node's attribute features to produce the node representation. The node representations stemming from the two types of edge connections are combined via a normalized sum and passed through the ReLU activation function to derive the final node embedding. This study specifies the number of hidden layers as 2, indicating that the model predicts the line category based on aggregated information from its 1- and 2-hop neighbors.



(a) General structure of the proposed GraphSAGE-based line classification model



(b) Structure of the proposed hetero-GraphSAGE layer

Figure 4. Structure of the proposed GraphSAGE-based line classification model

4 Experiment

To verify the feasibility of the proposed method, actual engineering drawings from the FloorPlanCAD (Fan et al., 2021) dataset were employed for the experimentation. The subsequent sections detail the dataset processing, experimental setup and results.

4.1 Experiment Setup

This section elaborates on dataset processing method, model parameters, experimental environment and evaluation metrics.

(1) Dataset processing method

The FloorPlanCAD dataset stores actual engineering floor drawings in vectorized format, encompassing over 30 component categories within the drawings. Initially, certain components were excluded based on the study's focus. The object of this study is paper drawings of building floor plans, which should include basic building structural components and annotation elements. Thus, this study separated the line categories as wall contour lines (Wall), annotation lines (Annotation), axis lines (Axis) and other lines (Others). The purpose of choosing these categories is that walls are structural backbone of buildings, with other elements like doors and windows typically attached to walls. Axis lines offer component coordinates concerning the building's coordinate system, while annotation lines furnish precise dimensional parameters for components. Furthermore, this study assumed that furniture and décor with specific range and countable instances could be removed by adding masks during preprocessing stage (such as instance segmentation-based pre-processing). Therefore, this study removed the furniture and decoration category components, as well as anomalous samples such as blank drawings during dataset processing.

The filtered vectorized drawings were exported into raster drawings to simulate scanned versions of ageing building's paper drawings. Subsequently, employing the proposed vectorization and graph construction method described in Section 3, the line elements in each drawing are extracted and used to construct the graph structure. Finally, this study constructs a dataset including 2046 graphs. The statistics of the node number of each category are shown in Table 2. The training and test sets are divided from these graphs at a ratio of 4:1.

Table 2. The quantity of each category of nodes

Category	Wall	Axis	Annotation	Others
Number of nodes	132753	56696	46492	70942
Proportion of node（%）	43.26	18.47	15.15	23.12

(2) Model parameters

Using the GraphSAGE-based model structure described in Section 3.3, this study trains a line classification model (Hetero GraphSAGE) to predict categories of line elements on drawing. In addition to the Hetero GraphSAGE model, a baseline model (Baseline) adapting to homogeneous graph is introduced in the experiment. The dataset for Baseline model only encompasses adjacent edges, aligning with previous studies (W. Zhang et al., 2023). For the nodal features of the baseline model, relevant research primarily focuses on the geometric attributes of line elements when constructing nodal features (W. Zhang et al., 2023). Since there is no relevant research using exactly the same vectorization method as this study, the nodal features proposed by these studies cannot be directly applied to baseline model. Consequently, the nodal features of the baseline model are confined to Position, Dimension, and Angle attributes as specified in Table 1. To maintain a fair comparison, the two models are designed to have similar structure and depth, which detailed by:

Hetero GraphSAGE: 2 Hetero GraphSAGE convolutional layers for hidden layers+1 linear layer+1 output layer, each hidden layer has 256 nodes (each kind of edge has 128 nodes). 2×ReLU+1×Logsoftmax as nonlinear activation functions.

Baseline: 2 GraphSAGE convolutional layers for hidden layers+1 linear layer+1 output layer, each hidden layer has 256 nodes. 2×ReLU+1×Logsoftmax as nonlinear activation functions.

(3) Experimental environment

The experimental environment is Ubuntu 22.04, an i7-13700kf processer, an RTX 4090 graphics card, 32 GB of ram, Python 3.8, PyTorch 2.0.1 and PyTroch Geometric 2.5.2. In this study, a strategy of progressively decreasing the learning rate over multiple training iterations is employed. The optimizer utilized is Adaptive Moment Estimation (Adam). Across three training phases, the model is trained for [200, 3000, 3000] epochs, with the learning rate for each phase set at [0.01, 0.001, 0.0005]. Additionally, weight decay is incorporated with values of [5e-4, 5e-5, 5e-6] for the respective training rounds.

(4) Evaluation metrics

The recall (R) and precision (P)is used to evaluate the model performance, which are defined as:

$$P = \frac{TP}{TP+FP} \tag{2}$$

$$R = \frac{TP}{TP+FN} \tag{3}$$

Moreover, the F1 score (F_1) is used to measure the overall performance of line classification model, which is defined as:

$$F_1 = \frac{2\times P\times R}{P+R} \tag{4}$$

4.2 Experimental Results

This section presents the line classification results of the proposed Hetero GraphSAGE model and comparison with the Baseline model.

(1) Line classification results

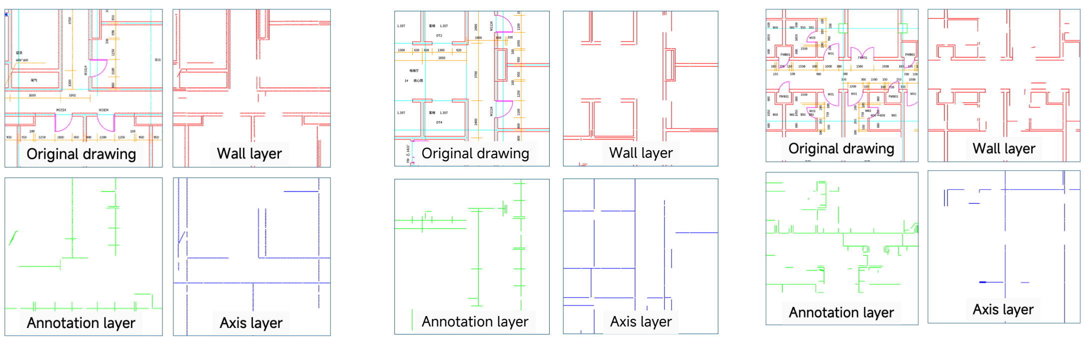
The quantitative results of the Hetero GraphSAGE model are shown in Table 3. The results show that the F_1 indicators of wall, annotation and others exceed 0.75, with good performance in the line classification task. Notably, the r indicator of wall stands at 0.84, indicating the model's proficiency in predicting most wall contour lines from paper drawings, providing an accurate reference for other components in BIM reconstruction. In terms of p indicators, the model exhibits the highest precision in predicting the annotation category, facilitating the precise restoration of geometric data. However, the model did not perform as well in predicting axis lines. This can be attributed to the fact that axis tend to coexist with walls in the drawings, as well as the lack of distinctive features of the axis in the absence of axis tags. Additionally, the imbalance in the dataset affects the prediction results for the axis category due to the relatively small number of axes in the dataset. The model demonstrates relatively strong predictive performance in the others category, aiding in filtering out extraneous components (such as doors and windows) prior to extracting wall information. The classification outcomes for others lines can be effectively integrated with object detection or instance segmentation methodologies to extract architectural component information efficiently.

Table 3. Quantitative results on the proposed dataset of Hetero GraphSAGE model

Indicators	Wall	Axis	Annotation	Others	F_1
r	0.842	0.625	0.743	0.736	-

Indicators	Wall	Axis	Annotation	Others	F_1
p	0.759	0.731	0.785	0.774	-
F_1	0.799	0.674	0.763	0.755	0.748

The qualitative results of the Hetero GraphSAGE model are illustrated in Figure 5. The model effectively classifies the wall lines. While some of the short edge contours of the wall may be missing, the accurately categorized lines are a good representation of the contours and extent of the wall. The result of annotation line classification in the left-bottom of Figure 5 (c) shows the model performs well even in a relatively line dense drawing. However, errors in classification become more prevalent when the distance between wall lines and annotation lines is minimal, thereby impacting the continuity of the local wall contour. Errors in axis line classification commonly arise when axis lines intersect walls. Notably, when axis lines are encircled by numerical texts, they are prone to misclassification as annotation lines, as exemplified in Figure 5 (c).



(a) Sample 1 (b) Sample 2 (c) Sample 3

Figure 5. Qualitative results of the Hetero GraphSAGE model

(2) Baseline comparison

In order to demonstrate the significance of the introduced nodal features and heterogeneous graph structure in enhancing line classification accuracy, an experiment involving the baseline model is conducted. The F_1 indicators are used to assess model performance, and the comparative results between the baseline model and the proposed Hetero GraphSAGE model are detailed in Table 4. The results indicate that Hetero GraphSAGE model outperforms Baseline model across all line classification categories. The overall performance in categorization tasks shows an enhancement of 0.102. The F_1 scores for wall, annotation and others line classification all exceeded 0.75. Particularly in the annotation category, the Hetero GraphSAGE model F_1 shows a 0.193 improvement over the Baseline model, which indicates the significance of integrating text-related nodal features and a heterogeneous graph structure in achieving superior classification accuracy.

Table 4. Comparison results for line classification performance of two models.

Categories	Wall	Axis	Annotation	Others	F_1
Baseline	0.736	0.597	0.570	0.682	0.646
Hetero GraphSAGE	**0.799**	**0.674**	**0.763**	**0.755**	**0.748**

5 Discussion

This study proposes a high accuracy automatic line classification method for the paper drawing layering process in BIM reconstruction. As mentioned in the previous section, most line elements in drawings can be accurately classified. This section will analyze the effect of the proposed nodal feature list and heterogeneous graph structure on the line classification performance, as well as the shortcomings of current research.

(1) Effect of nodal feature list on line classification task

The proposed nodal feature list plays an important role in encoding line element geometric attributes and topological relationship with nearby texts. To illustrate the effectiveness of these text-relevant features, a comparative experiment was conducted to assess the performance of the Hetero GraphSAGE model using different nodal features. The two models used for comparison have the same structure, the "WithText" model, trained on the proposed nodal features including text-relevant attributes, and the "WithoutText" model, trained on a dataset devoid of text-relevant nodal features as detailed in

Table 1 (encompassing only Position, Dimension, and Angle features). The results are shown in Table 5, the integration of text-relevant features leads to a slight improvement in the classification performance of wall, axis, and other categories of lines. Notably, the performance in annotating line classification sees a substantial enhancement of nearly 0.14 with the inclusion of text-relevant features. Furthermore, the overall performance witnesses an improvement of approximately 0.15 upon the introduction of these text-relevant features, which proves the effectiveness of the proposed nodal feature list.

Table 5. Comparison results for F_1 of the models trained with different nodal features

Categories	Wall	Axis	Annotation	Others	F_1
WithText	**0.799**	**0.674**	**0.763**	**0.755**	**0.748**
WithoutText	0.781	0.652	0.624	0.727	0.696

(2) Effect of the heterogeneous graph structure on line classification task

The incorporation of a heterogeneous graph structure serves as an additional strategy to enhance line classification performance. In order to evaluate the impact of this heterogeneous graph structure on line classification accuracy, both the Hetero GraphSAGE model (Hetero) and the Baseline model (Homo) were trained on identical datasets, the results are shown in Table 6. The results highlight that the influence of the graph structure on annotation line classification is relatively minor compared to other categories. The enhancement in predicting annotation lines primarily stems from the inclusion of text-relevant features. However, for wall, axis, and other line classifications, there is an improvement ranging from approximately 0.05 to 0.07. Overall, the heterogeneous model demonstrates a 0.05 enhancement in performance, shows the effectiveness of the proposed heterogeneous graph structure.

Table 6. Comparison results for F_1 of models on different graph structure

Categories	Wall	Axis	Annotation	Others	F1
Hetero	**0.799**	**0.674**	**0.763**	**0.755**	**0.748**
Homo	0.750	0.600	0.748	0.693	0.698

(3) Limitations and future work

Even though the experiments have demonstrated that the proposed method can improve the line classification accuracy thereby supporting the paper drawing layering pre-processing in ageing building BIM reconstruction, the current study still has some limitations.

Firstly, although the proposed method can correctly classify most of the wall lines, the margin represented by short lines are often missing, which will affect the subsequent contour detection. The primary reason is that current drawing vectorization method is designed to filter out line segments that are too short to reduce the noise caused by text contour, however, current strategy also causes some information loss. The line missing problem also causes losing of adjacent connection relationship, potentially affect the classification accuracy. Future study could focus on refining the drawing vectorization method to address text interference more effectively. Secondly, the study employs a uniform nodal feature list for all line categories, overlooking distinctive features like axis tags and annotation line arrows that provide clear hints for line categorization. Future endeavors could explore integrating object detection methods to extract these features beforehand, thus enhancing the classification performance of relevant lines. Finally, current text-relevant nodal features only distinguish text types as numeric and nonameric. The semantic type of the text, such as dimension text, category text requires be further analyzed and encoded to the nodal feature list. Moreover, the improvement of the proposed line classification method on the downstream information extraction accuracy, such as building components object detection task, will be quantitatively evaluated in future work.

6 Conclusions

BIM reconstruction plays an important role in enabling smart O&M practices for aging buildings. However, the low efficiency of paper drawing layering pre-processing affects the practical application of BIM reconstruction. To address this challenge, this study proposes a heterogeneous GNN-based paper drawing line classification method to improve the drawing layering efficiency. Compared to existing studies, the proposed method has the following innovations. Firstly, the nodal feature list incorporates not only the geometric attributes of the line itself but also its relationship with nearby text elements, thereby improving the ability of node features to represent the properties of different categories of lines. Secondly, the proposed heterogeneous graph structure captures the complex topological relationships among lines by representing the adjacent and parallel relationship using different types of edge. Finally, the Hetero GraphSAGE model structure is proposed for conducting the line classification task on heterogeneous graph. Experimental results reveal that the model achieves a F_1 score of 0.748 in the line classification task and yields superior performance compared to the baseline model. In conclusion, the proposed method improves the efficiency and accuracy of paper drawing layering pre-processing. It will also provide a reliable information extraction tool to aid in the BIM reconstruction of ageing buildings.

ACKNOWLEDGMENTS

This work was supported by the Innovation and Technology Fund Seed Research Project (ITS/070/22), the Innovation and Technology Fund Platform Research Projects (ITP/002/22LP), and the Guangdong Basic and Applied Basic Research Foundation (2022B1515130006).

References

de Wilde, P. (2019). Ten questions concerning building performance analysis. *Building and Environment*, *153*, 110–117. https://doi.org/10.1016/j.buildenv.2019.02.019

Fan, Z., Zhu, L., Li, H., Chen, X., Zhu, S., & Tan, P. (2021). FloorPlanCAD: A Large-Scale CAD Drawing Dataset for Panoptic Symbol Spotting. *2021 IEEE/CVF International Conference on Computer Vision (ICCV)*, 10108–10117. https://doi.org/10.1109/ICCV48922.2021.00997

Feng, Y., Wang, J., Fan, H., & Hu, Y. (2021). A BIM-Based Coordination Support System for Emergency Response. *IEEE Access*, *9*, 68814–68825. IEEE Access. https://doi.org/10.1109/ACCESS.2021.3077237

Grompone von Gioi, R., Jakubowicz, J., Morel, J.-M., & Randall, G. (2010). LSD: A Fast Line Segment Detector with a False Detection Control. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *32*(4), 722–732. IEEE Transactions on Pattern Analysis and Machine Intelligence. https://doi.org/10.1109/TPAMI.2008.300

Hamilton, W. L., Ying, R., & Leskovec, J. (2017). Inductive representation learning on large graphs. *Proceedings of the 31st International Conference on Neural Information Processing Systems*, 1025–1035.

Hu, Z.-Z., Leng, S., Lin, J.-R., Li, S.-W., & Xiao, Y.-Q. (2022). Knowledge Extraction and Discovery Based on BIM: A Critical Review and Future Directions. *Archives of Computational Methods in Engineering*, *29*(1), 335–356. https://doi.org/10.1007/s11831-021-09576-9

Hu, Z.-Z., Zhang, J.-P., Yu, F.-Q., Tian, P.-L., & Xiang, X.-S. (2016). Construction and facility management of large MEP projects using a multi-Scale building information model. *Advances in Engineering Software*, *100*, 215–230. https://doi.org/10.1016/j.advengsoft.2016.07.006

Kamel, E., & Memari, A. M. (2019). Review of BIM's application in energy simulation: Tools, issues, and solutions. *Automation in Construction*, *97*, 164–180. https://doi.org/10.1016/j.autcon.2018.11.008

Kang, S.-O., Lee, E.-B., & Baek, H.-K. (2019). A Digitization and Conversion Tool for Imaged Drawings to Intelligent Piping and Instrumentation Diagrams (P&ID). *Energies*, *12*(13), Article 13. https://doi.org/10.3390/en12132593

Kim, H., Lee, W., Kim, M., Moon, Y., Lee, T., Cho, M., & Mun, D. (2021). Deep-learning-based recognition of symbols and texts at an industrially applicable level from images of high-density piping and instrumentation diagrams. *Expert Systems with Applications*, *183*, 115337. https://doi.org/10.1016/j.eswa.2021.115337

Lin J., Zhou Y., Zheng Z., & Lu X. (2023). Research and application of intelligent design review. *Engineering Mechanics*, *40*(7), 25–38. https://doi.org/10.6052/j.issn.1000-4750.2021.11.0908

Moon, Y., Han, S.-T., Lee, J., & Mun, D. (2023). Extraction of line objects from piping and instrumentation diagrams using an improved continuous line detection algorithm. *Journal of Mechanical Science and Technology*, *37*(4), 1959–1972. https://doi.org/10.1007/s12206-023-0333-9

Moon, Y., Lee, J., Mun, D., & Lim, S. (2021). Deep Learning-Based Method to Recognize Line Objects and Flow Arrows from Image-Format Piping and Instrumentation Diagrams for Digitization. *Applied Sciences*, *11*(21), Article 21. https://doi.org/10.3390/app112110054

Moreno-García, C. F., Elyan, E., & Jayne, C. (2017). Heuristics-Based Detection to Improve Text/Graphics Segmentation in Complex Engineering Drawings. In G. Boracchi, L. Iliadis, C. Jayne,

& A. Likas (Eds.), *Engineering Applications of Neural Networks* (pp. 87–98). Springer International Publishing. https://doi.org/10.1007/978-3-319-65172-9_8

Pan, Z., Yu, Y., Xiao, F., & Zhang, J. (2023). Recovering building information model from 2D drawings for mechanical, electrical and plumbing systems of ageing buildings. *Automation in Construction*, *152*, 104914. https://doi.org/10.1016/j.autcon.2023.104914

Xie, L., Lu, Y., Furuhata, T., Yamakawa, S., Zhang, W., Regmi, A., Kara, L., & Shimada, K. (2022). Graph neural network-enabled manufacturing method classification from engineering drawings. *Computers in Industry*, *142*, 103697. https://doi.org/10.1016/j.compind.2022.103697

Xu, Z., Jha, N., Mehadi, S., & Mandal, M. (2024). Multiscale object detection on complex architectural floor plans. *Automation in Construction*, *165*, 105486. https://doi.org/10.1016/j.autcon.2024.105486

Yin, M., Tang, L., Zhou, T., Wen, Y., Xu, R., & Deng, W. (2020). Automatic layer classification method-based elevation recognition in architectural drawings for reconstruction of 3D BIM models. *Automation in Construction*, *113*, 103082. https://doi.org/10.1016/j.autcon.2020.103082

Zhang, T. Y., & Suen, C. Y. (1984). A fast parallel algorithm for thinning digital patterns. *Communications of the ACM*, *27*(3), 236–239. https://doi.org/10.1145/357994.358023

Zhang, W., Joseph, J., Yin, Y., Xie, L., Furuhata, T., Yamakawa, S., Shimada, K., & Kara, L. B. (2023). Component segmentation of engineering drawings using Graph Convolutional Networks. *Computers in Industry*, *147*, 103885. https://doi.org/10.1016/j.compind.2023.103885

Zhao, Y., Deng, X., & Lai, H. (2021). Reconstructing BIM from 2D structural drawings for existing buildings. *Automation in Construction*, *128*, 103750. https://doi.org/10.1016/j.autcon.2021.103750