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TWO-BRANCH FEATURE EXTRACTION WITH SEMANTIC ENRICHMENT FOR BUILDING INFORMATION MODELING OBJECT CLASSIFICATION USING AI MODELS

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***Abstract*— In this work, two-branch feature extraction with semantic enrichment for Building Information Modeling (BIM) object classification using AI models is presented to address some problems associated with the existing BIM object classification and also improve cross-disciplinary collaboration all through building projects' lifecycle through semantic content enrichment. First the IFCNet dataset which has 20 different BIM object classes that are stored in IFC file format, with about 95,160 data samples was obtained and subjected to series of data preprocessing procedures. Then, the two-branch feature extraction which include geometric feature extraction of the BIM object using 3D Convolutional Neural Network (CNN) and the relational feature extraction of the BIM object using Convolutional Neural Network (CNN) were conducted. The fusion of the geometric features and the relational features using Convolutional Neural Network (CNN) was done to generate a unified BIM object description. Next, the unified BIM object description was used as input for the BIM object classification using Convolutional Neural Network (CNN). The results show that the CNN model has average prediction accuracy of 84.74% along with precision, recall and F1 score values of 85.86%, 84.74% and 84.97% respectively. Also the classification model in this work performed better that the published BIM object classification model presented by other researchers which has prediction accuracy of 83.20%. The ideas presented in this work is very essential to enhance collaboration among the various stakeholders always involved in building project lifecycle. .**

Keywords*— *Feature Extraction, Semantic Enrichment, Geometric Feature, Building Information Modeling Relational Feature, BIM Object Classification, AI Models

1. Introduction

One of the primary challenges in Building Information Modeling (BIM) adoption is the lack of automated, standardized methods for classifying BIM objects, especially in complex MEP systems (Alam, et al., 2023; Kineber, et al., 2023). Existing classification processes are largely manual, which is time-consuming and prone to errors (Morais et al., 2022). Moreover, many BIM objects lack rich semantic context, which limits their usefulness throughout the lifecycle of a building (Dinis et al., 2022). As a result, data fragmentation, miscommunication and inefficiencies persist across construction teams, leading to project delays and higher costs (Marsh, 2024; Latif, et al.,2023; Alzeraa, 2018).The problem is particularly critical for MEP systems, where complex interdependencies and diverse components are often poorly represented in BIM models. To address this, there is a need for intelligent systems capable of classifying objects correctly and enhancing their semantic content for better cross-disciplinary collaboration.

Despite the growing adoption of BIM in the Architecture, Engineering and Construction (AEC) industry, the classification of BIM objects remains a significant challenge, especially for complex systems like MEP. The current methods are often manual, inconsistent and inefficient, leading to errors and delays in the construction process (Mophethe, 2024). Additionally, the lack of semantic enrichment of BIM data results in limited utility for stakeholders throughout the project lifecycle (Dinis *et al.*, 2022). The MEP domain, in particular, presents unique challenges due to its intricate components and interdependencies. Existing BIM models often fail to fully capture the complexity of these systems, resulting in poor data representation and difficulty in managing MEP systems during design, construction and operation (Teo *et al.*, 2022). This research aims to address these challenges by developing an AI-based classification model and a semantic enrichment framework that will automate the classification process and improve the contextual information associated with BIM objects.

2. Methodology

In this work, a two-branch feature extraction with semantic enrichment for building information modeling object classification using AI-models is presented. The system model for the study is presented in Figure 1. According to the system model in Figure 1, the two-branch feature extraction consists of the geometric feature extraction model and the relational feature extraction model; the BIM object description output from the two branches are then fused together by the feature fusion model to obtained a unified BIM object description which serves as input to the BIM object classification model and the semantic enrichment module. Also, the BIM object classification output is fed into the semantic enrichment module as the second input and then the semantic enrichment module utilizes the two inputs for the sematic enrichment purpose.

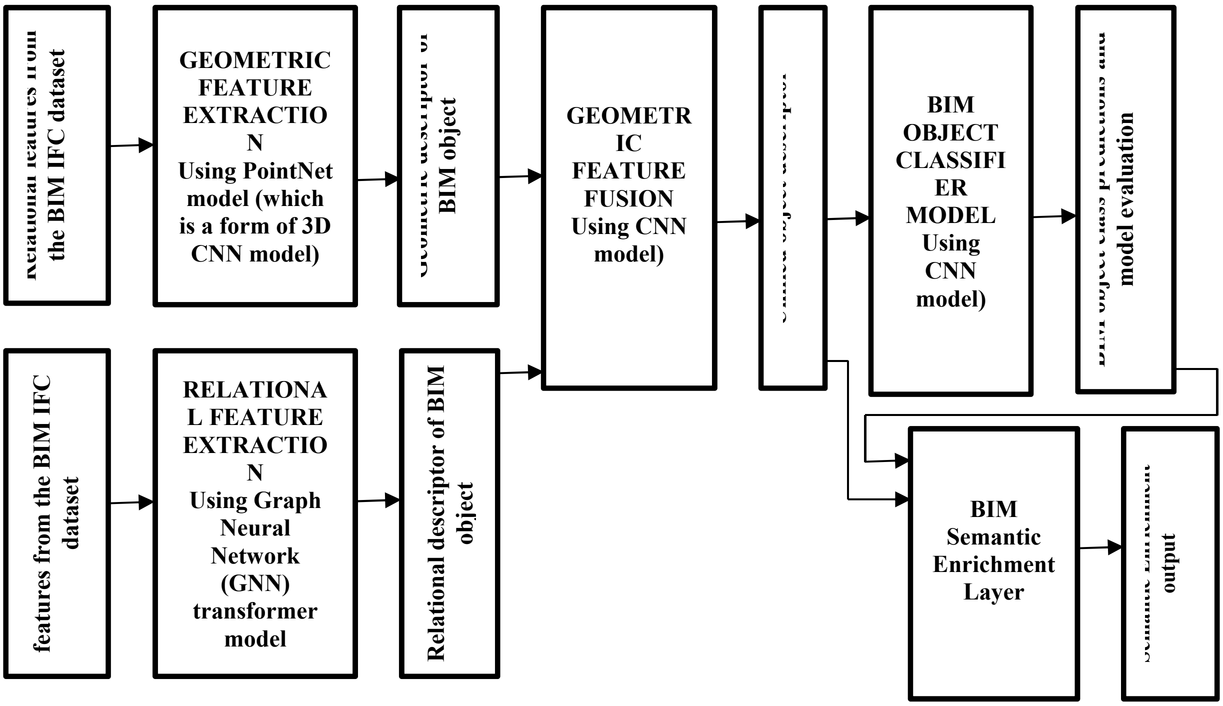

Figure 1 The system model for the two-branch feature extraction with semantic enrichment for BIM object classification

The geometric feature extraction is conducted using the details of the PointNet which is a form of 3D CNN (Convolutional Neural Network) model. The details of the PointNet model is presented in Figure 3. The relational feature extraction is conducted using Graph Neural Network Transformer model and the flow diagram for the relational feature extraction is presented in Figure 4. Similarly, the flow diagram for the semantic enrichment layer is presented in Figure 5.

The annotated flow diagram for the system model is presented in Figure 2. The system requires five major steps that begins in step 1 with acquisition and preprocessing of the IFCNet dataset for the BIM objects. In step 2, the IFCNet dataset, the data items for each of the BIM objects are stored in IFC (Industry Foundation Classes) format. The feature extraction using two-branch feature extraction approach is performed in the step 2 which gives geometric feature description and relational feature description of the BIM object.

The BIM geometric feature extractor model takes point cloud data input while the relational features (are presented as edge maps using gradient-based detection) to the relational feature extractor model. In step 3, feature fusion which produce unified BIM object description is carried out. The unified BIM object description from the feature fusion model is fed to the BIM object classification model and then the classification model is trained to predict the BIM objects in step 4. Finally, in step 5, the semantic enrichment module takes input from the feature fusion model and the BIM object classification model and use the two inputs to generate the required semantic enrichment outputs.

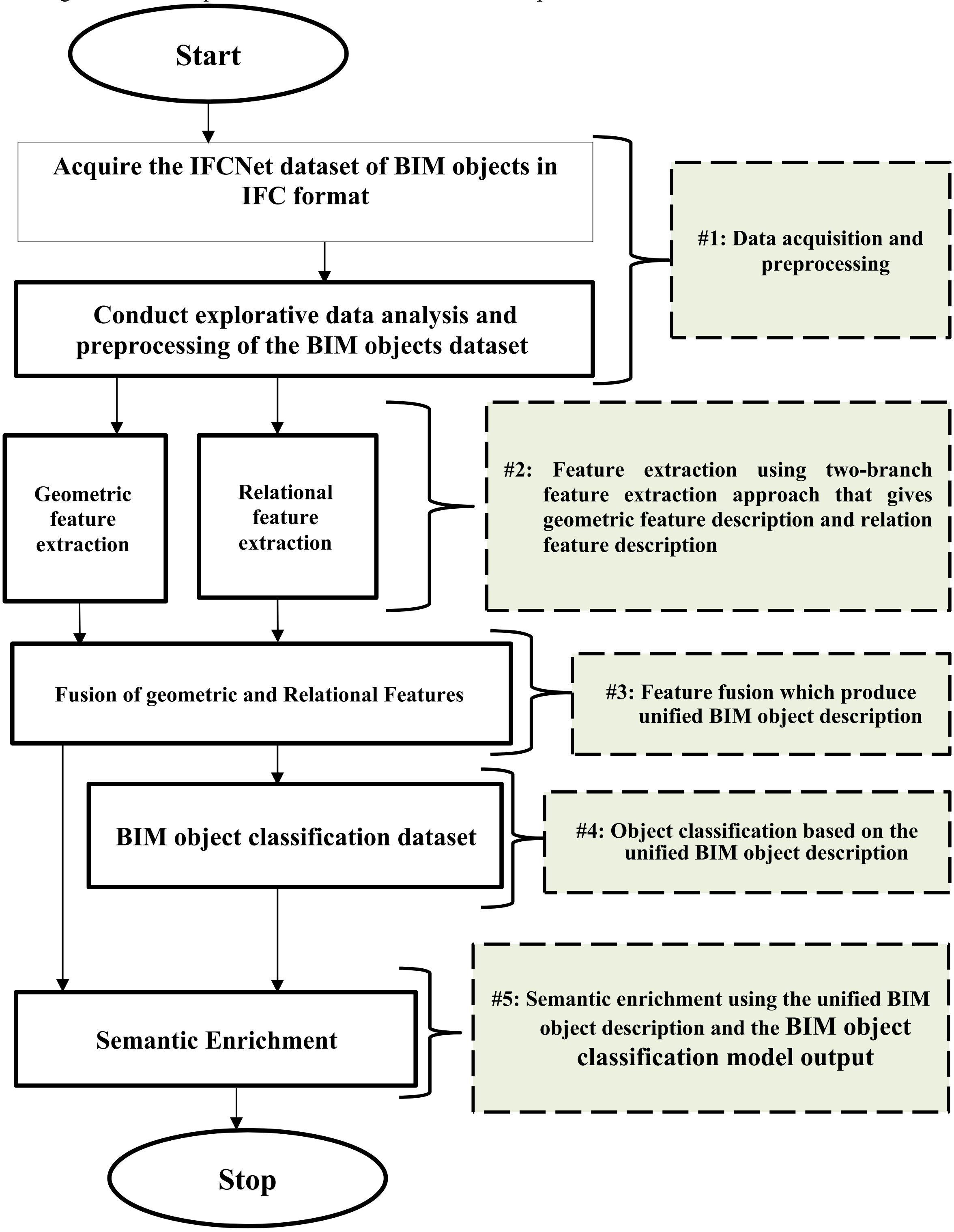

Figure 2 The annotated flow diagram for the system model

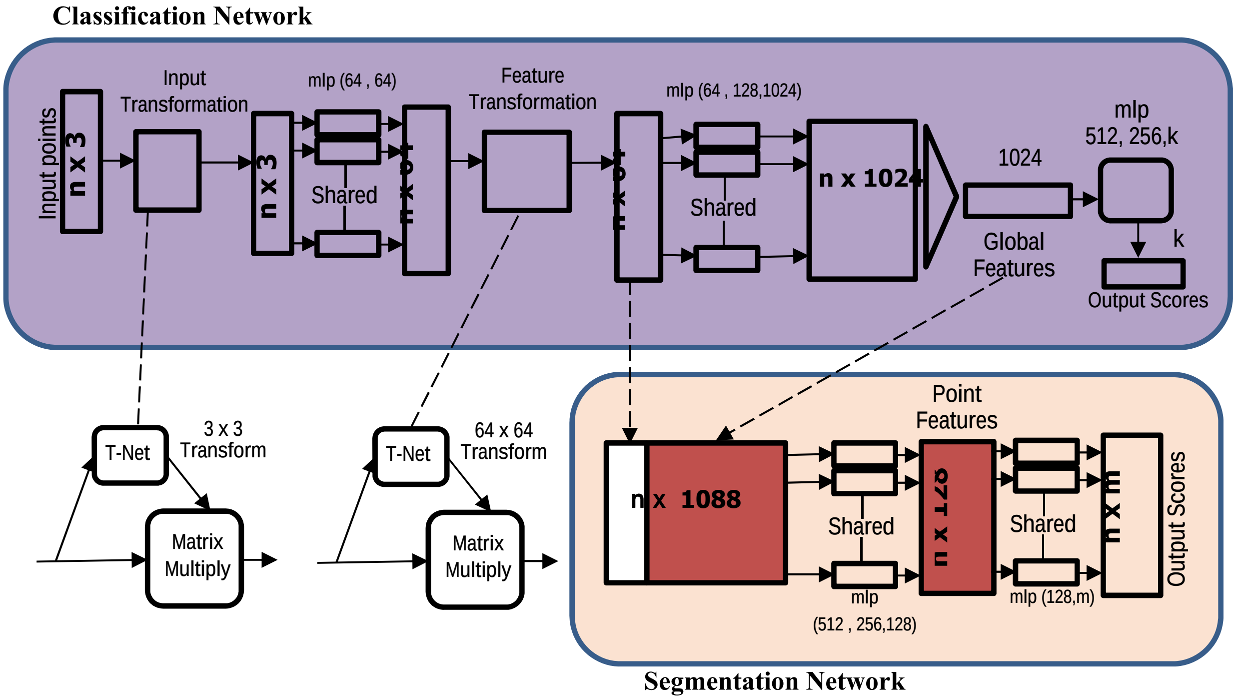

Figure 3 The PointNet Geometric Feature Extraction Model Architecture (Adapted from Qi *et al.*, 2017)

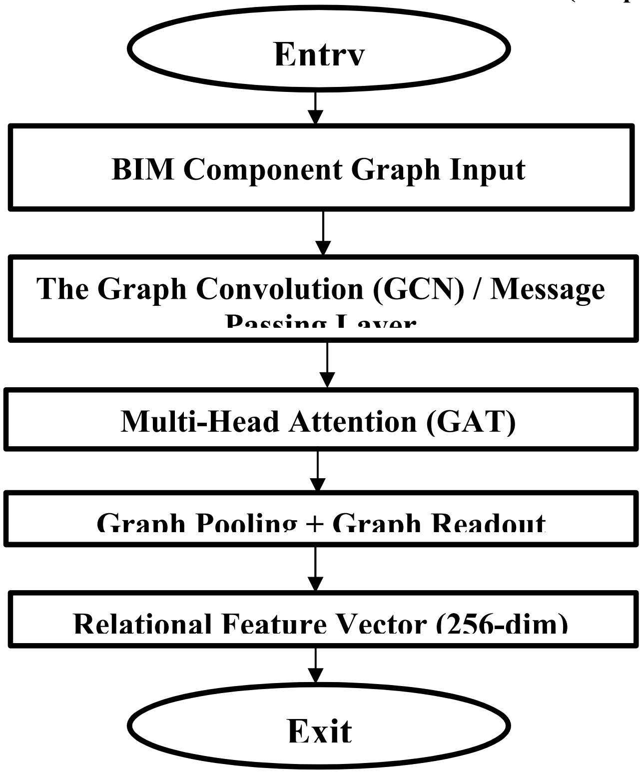

Figure 4 The flow diagram for the relational feature extraction using the Graph Neural Network Transformer model

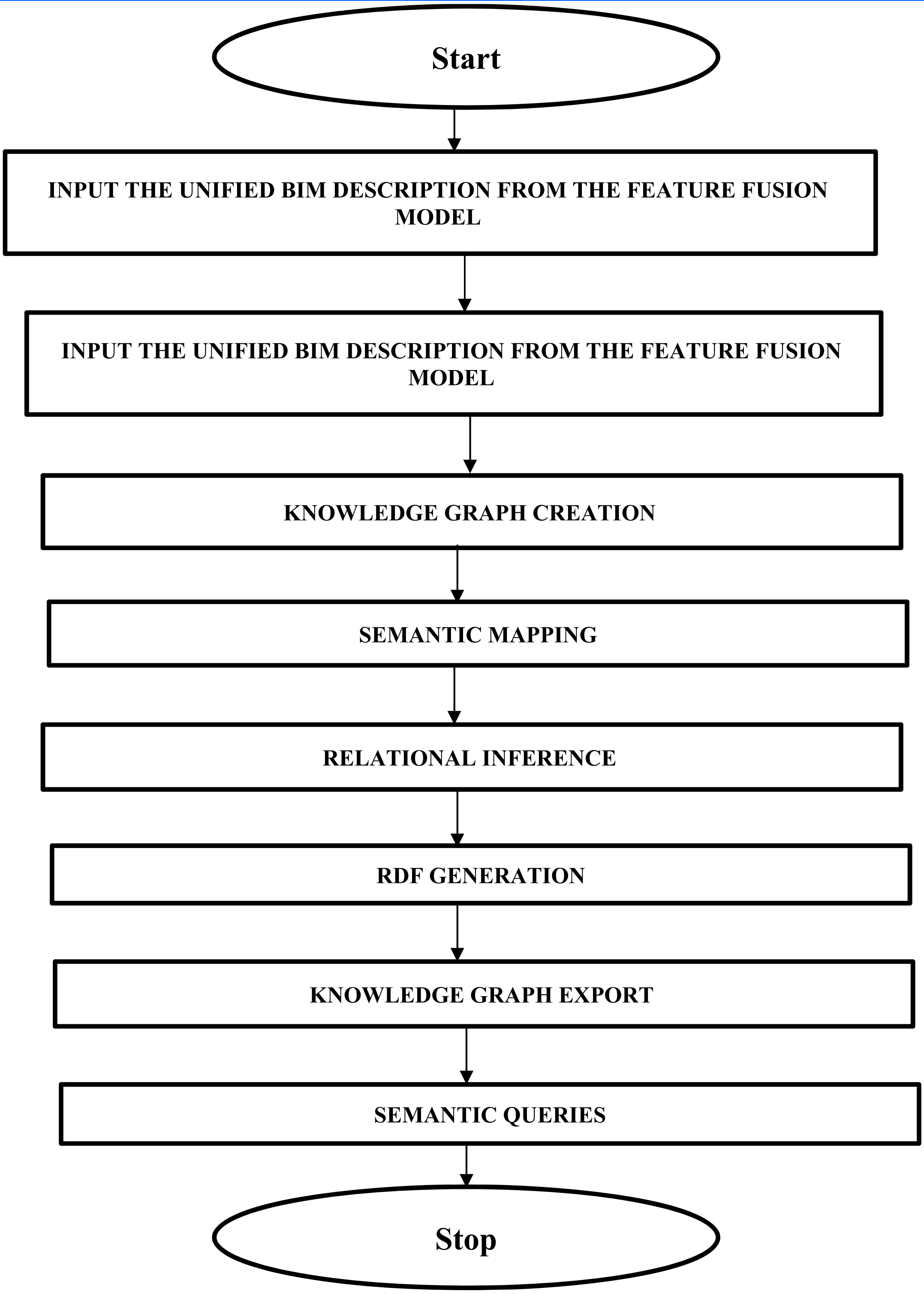

Figure 5 The flow diagram for the semantic enrichment layer

3. Results and Discussion

The case study IFCNet dataset used has 95160 BIM object samples with 20 different BIM object classes as shown in Table 1. The pie chart showing the imbalanced data samples distribution among the 20 BIM object classes before the data balancing is applied is shown in Figure 6 while balanced BIM object class distribution is shown in Figure 7. In the balanced dataset, a total of 12,000 data samples are used with each of the 20 BIM object classes having 600 data samples. Essentially, the original dataset was under sampled to ensure that each of the 20 data classes is equally represented in the balanced dataset used for the model training and validation.

Table 1 The distribution of the data samples among the 20 different BIM object classes in the case study IFCNet dataset

S/N	BIM Element Class	Number of Samples	Category
1	DuctFitting	7800	MEP Component
2	PipeSegment	7788	MEP Component
3	PipeFitting	7776	MEP Component
4	DuctSegment	6372	MEP Component
5	CableCarrierSegment	6348	Electrical Component
6	Plate	6276	Structural/Architectural
7	CableCarrierFitting	6192	Electrical Component
8	Wall	6444	Architectural Element
9	Slab	6084	Structural Element
10	AirTerminal	5700	MEP Component
11	SanitaryTerminal	5424	MEP Component
12	Railing	5064	Architectural Element
13	Valve	4152	MEP Component
14	Door	3708	Architectural Element
15	Beam	3384	Structural Element
16	Furniture	2688	Interior Element
17	SpaceHeater	1524	MEP Component
18	Lamp	1104	Electrical Component
19	Outlet	708	Electrical Component
20	Stair	624	Architectural/Circulation

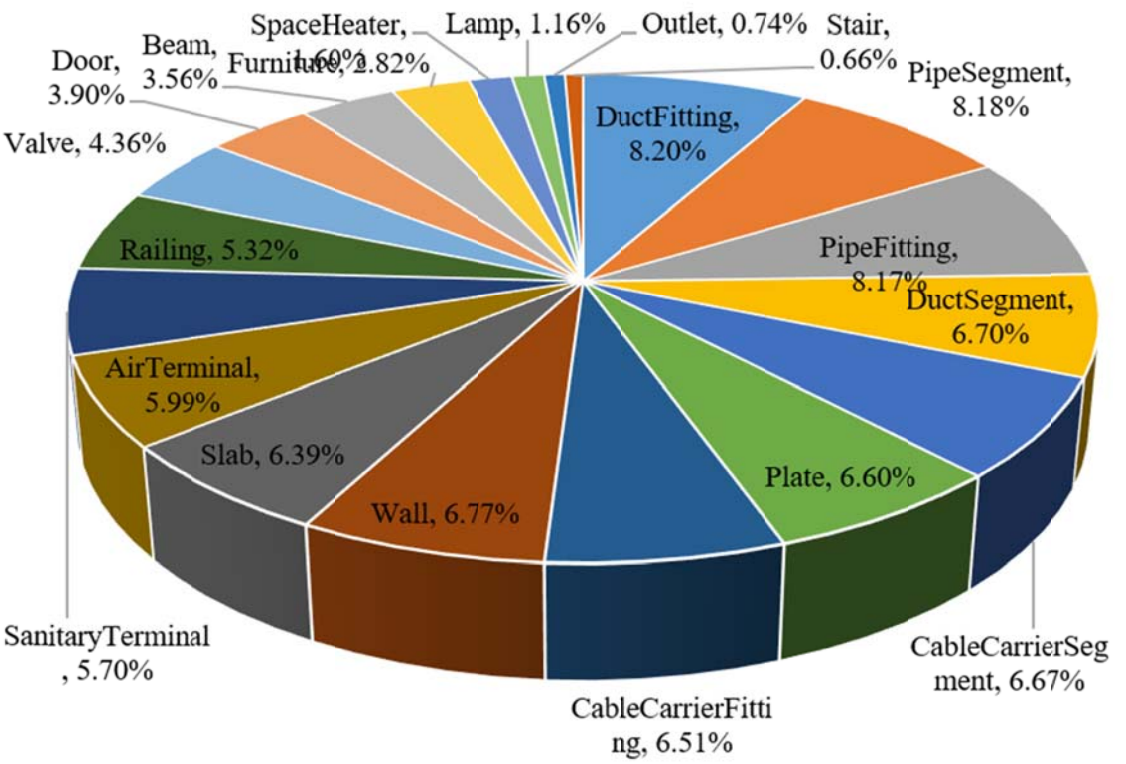

Figure 6 The pie chart showing the composition of the dataset in percentage of the 20 BIM object sorted by the object class balancing

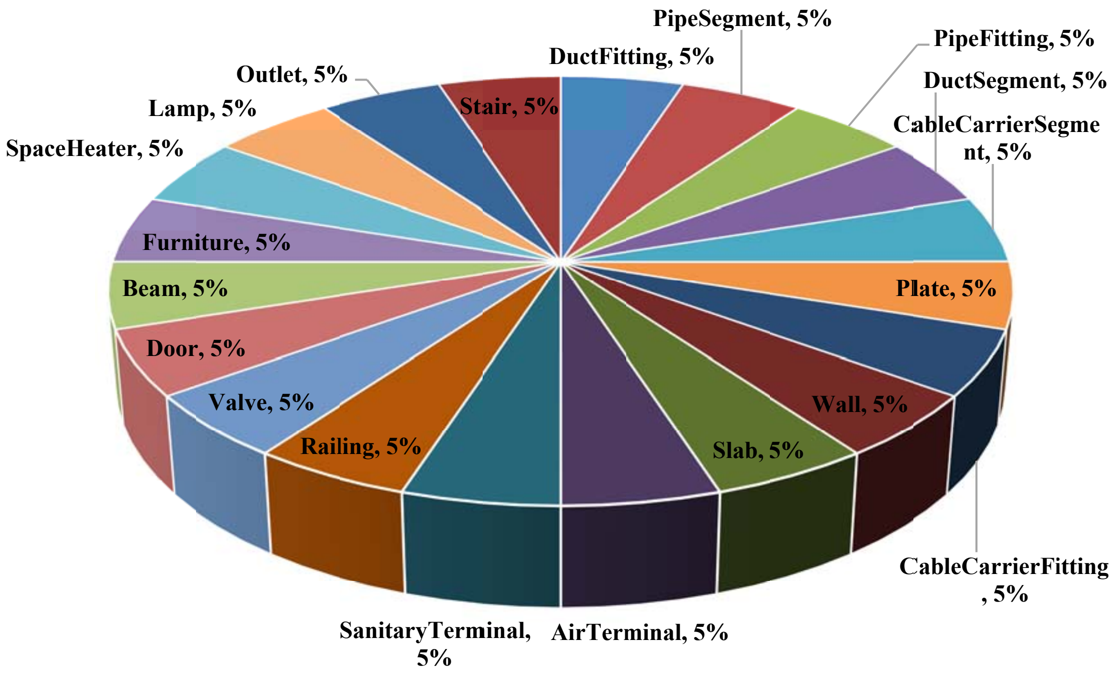

Figure 7 The pie chart for the balanced dataset showing the percentage of image samples per BIM element class

The class-wise performance metrics for PointNet geometric feature extraction model is presented in Table 2. The results show that the PointNet model has average prediction accuracy of 96.56 %. However, the precision, recall and F1 score are relatively lower with values of 63.50 %, 59.06 % and 59.92 %, respectively. This calls for other approaches that can be used to enhance the BIM object classification model.

Similarly, the class-wise performance metrics for graph neural network transformer (GNN) model used for the relational feature extraction is presented in Table 3. The results show that the GNN transformer model has average prediction accuracy of 95.89%. However, the precision, recall and F1 score are relatively lower with values of 55.43%, 52.64% and 53.36% respectively. Again, this calls for other approaches that can be used to enhance the BIM object classification model. Accordingly, the fusion of the geometric and relation models is implemented and the class-wise performance metrics for the convolutional neural network (CNN) model used for the feature fusion is presented in Table 3. The results show that the CNN model has average prediction accuracy of 96.24%. The precision, recall and F1 score are 56.06%, 59.63% and 56.58% respectively.

Furthermore, the class-wise performance metrics for the convolutional neural network (CNN) model used for the BIM object classification is presented in Table 4. The results show that the CNN model has average prediction accuracy of 84.74%. In this case, the precision, recall and F1 score are relatively at per with values of 85.86%, 84.74% and 84.97% respectively. This results show enhanced prediction performance for the BIM object classification model which also performed better that the BIM object classification model presented by Seydgar et al. (2024) (Figure 8) which has prediction accuracy of 83.20%. Finally, the knowledge graph structure created through the semantic enrichment pipeline is presented in Figure 9. The knowledge graph shows some of the BIM elements along with the other BIM element each of element the elemnt is connected to. This graph is developed from the input obtained from the BIM object class classification model and the fused feature descriptor model. The information is also captured in the semantic database created as part of the semantic enrichment components; with the semantic database a query can be used to elicit those relational information and element's class information from the semantic database.

Table 2 Class-wise performance metrics for PointNet geometric feature extraction model

Class	Precision	Recall	F1-Score	Accuracy
AirTerminal	0.7647	0.6408	0.6973	0.9668
Beam	0.4521	0.3929	0.4204	0.9617
CableCarrierFitting	0.7847	0.729	0.7559	0.9693
CableCarrierSegment	0.6488	0.6855	0.6667	0.9542
Door	0.6917	0.8925	0.7793	0.9802
DuctFitting	0.6393	0.6	0.619	0.9394
DuctSegment	0.5369	0.5031	0.5195	0.9378
Furniture	0.569	0.4925	0.528	0.9752
Lamp	0.2727	0.1111	0.1579	0.9865
Outlet	1	0.3529	0.5217	0.9954
PipeFitting	0.7186	0.8557	0.7812	0.9609
PipeSegment	0.6767	0.8051	0.7354	0.9525
Plate	0.6122	0.5732	0.5921	0.9479
Railing	0.8182	0.7795	0.7984	0.979
SanitaryTerminal	0.7248	0.5809	0.6449	0.9634
Slab	0.6316	0.7895	0.7018	0.9571
SpaceHeater	0.2727	0.1579	0.2	0.9798
Stair	0.6923	0.5625	0.6207	0.9954
Valve	0.6094	0.75	0.6724	0.968
Wall	0.5844	0.559	0.5714	0.9432
Average for all the classes	**0.63504**	**0.59068**	**0.5992**	**0.965685**

Table 3 Class-wise performance metrics for the graph neural network transformer (GNN) model used for the relational feature extraction

Class	Precision	Recall	F1-Score	Accuracy
AirTerminal	0.5595	0.662	0.6065	0.9487
Beam	0.3218	0.3333	0.3275	0.9516
CableCarrierFitting	0.6667	0.5161	0.5818	0.9516
CableCarrierSegment	0.5181	0.6289	0.5682	0.9361
Door	0.7634	0.7634	0.7634	0.9815
DuctFitting	0.6494	0.5795	0.6125	0.9399
DuctSegment	0.4889	0.5535	0.5192	0.9315
Furniture	0.6829	0.4179	0.5185	0.9781
Lamp	0.2143	0.2222	0.2182	0.9819
Outlet	0.3571	0.2941	0.3226	0.9912
PipeFitting	0.6565	0.7784	0.7123	0.9487
PipeSegment	0.6193	0.6923	0.6538	0.9399
Plate	0.5948	0.5796	0.5871	0.9462
Railing	0.7849	0.5748	0.6636	0.9689
SanitaryTerminal	0.7317	0.4412	0.5505	0.9588
Slab	0.637	0.6118	0.6242	0.9529
SpaceHeater	0.0976	0.1053	0.1013	0.9701
Stair	0.5833	0.4375	0.5	0.9941
Valve	0.6364	0.7404	0.6844	0.9701
Wall	0.5217	0.5963	0.5565	0.9357
Average for all the classes	**0.554265**	**0.526425**	**0.533605**	**0.958875**

Table 4 **Class-wise performance metrics for the convolutional neural network (CNN) model used for the feature fusion**

Class	Precision	Recall	F1-Score	Accuracy
AirTerminal	0.6452	0.7407	0.6897	0.9622
Beam	0.5	0.3333	0.4	0.9685
CableCarrierFitting	0.75	0.7241	0.7368	0.9685
CableCarrierSegment	0.6389	0.697	0.6667	0.9517
Door	0.6	0.75	0.6667	0.9811
DuctFitting	0.6667	0.4348	0.5263	0.9244
DuctSegment	0.6207	0.5806	0.6	0.9496
Furniture	0.25	0.1538	0.1905	0.9643
Lamp	0.1667	0.25	0.2	0.9832
Outlet	0.2	0.5	0.2857	0.9895
PipeFitting	0.7949	0.7949	0.7949	0.9664
PipeSegment	0.5897	0.6765	0.6301	0.9433
Plate	0.6	0.6154	0.6076	0.9349
Railing	0.8333	0.7692	0.8	0.979
SanitaryTerminal	0.525	0.6563	0.5833	0.937
Slab	0.5789	0.6471	0.6111	0.9412
SpaceHeater	0.4	0.25	0.3077	0.9811
Stair	0.5	1	0.6667	0.9979
Valve	0.7647	0.7647	0.7647	0.9832
Wall	0.5882	0.5882	0.5882	0.9412
Average for all the classes	0.560645	0.59633	0.565835	0.96241

Table 5 **Class-wise performance metrics for the convolutional neural network (CNN) model used for the BIM object classification**

Class	Precision	Recall	F1_Score	Accuracy
AirTerminal	0.9615	0.9259	0.9434	0.9259
Beam	0.8125	0.7647	0.7879	0.7647
CableCarrierFitting	0.9167	0.9706	0.9429	0.9706
CableCarrierSegment	0.8056	0.9063	0.8529	0.9063
Door	0.95	0.95	0.95	0.95
DuctFitting	0.8889	0.9143	0.9014	0.9143
DuctSegment	0.8438	0.8182	0.8308	0.8182
Furniture	0.8	0.6667	0.7273	0.6667
Lamp	0.8333	1	0.9091	1
Outlet	0.8333	0.8333	0.8333	0.8333
PipeFitting	0.9231	0.9231	0.9231	0.9231
PipeSegment	0.7949	0.8857	0.8378	0.8857
Plate	0.8286	0.7632	0.7945	0.7632
Railing	0.9615	0.8929	0.9259	0.8929
SanitaryTerminal	0.85	0.8947	0.8718	0.8947
Slab	0.8148	0.7333	0.7719	0.7333
SpaceHeater	0.5	0.6	0.5455	0.6
Stair	1	0.6667	0.8	0.6667
Valve	1	0.96	0.9796	0.96
Wall	0.8529	0.8788	0.8657	0.8788
Average for all the classes	0.85857	0.84742	0.84974	0.84742

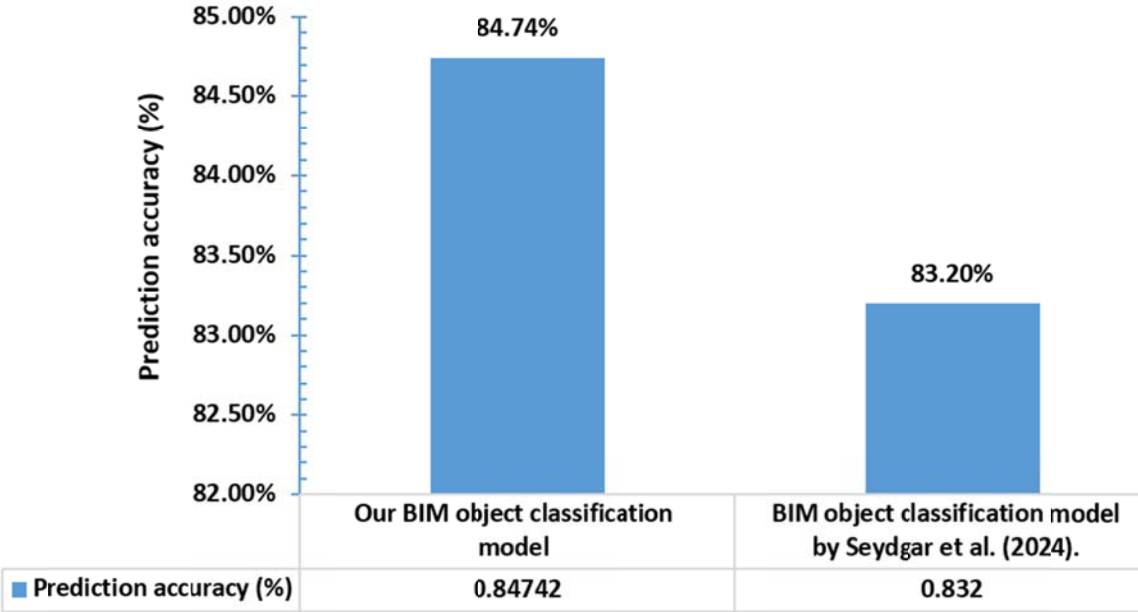

Figure 8 Comparison of results with the published work by Seydgar *et al.* (2024)

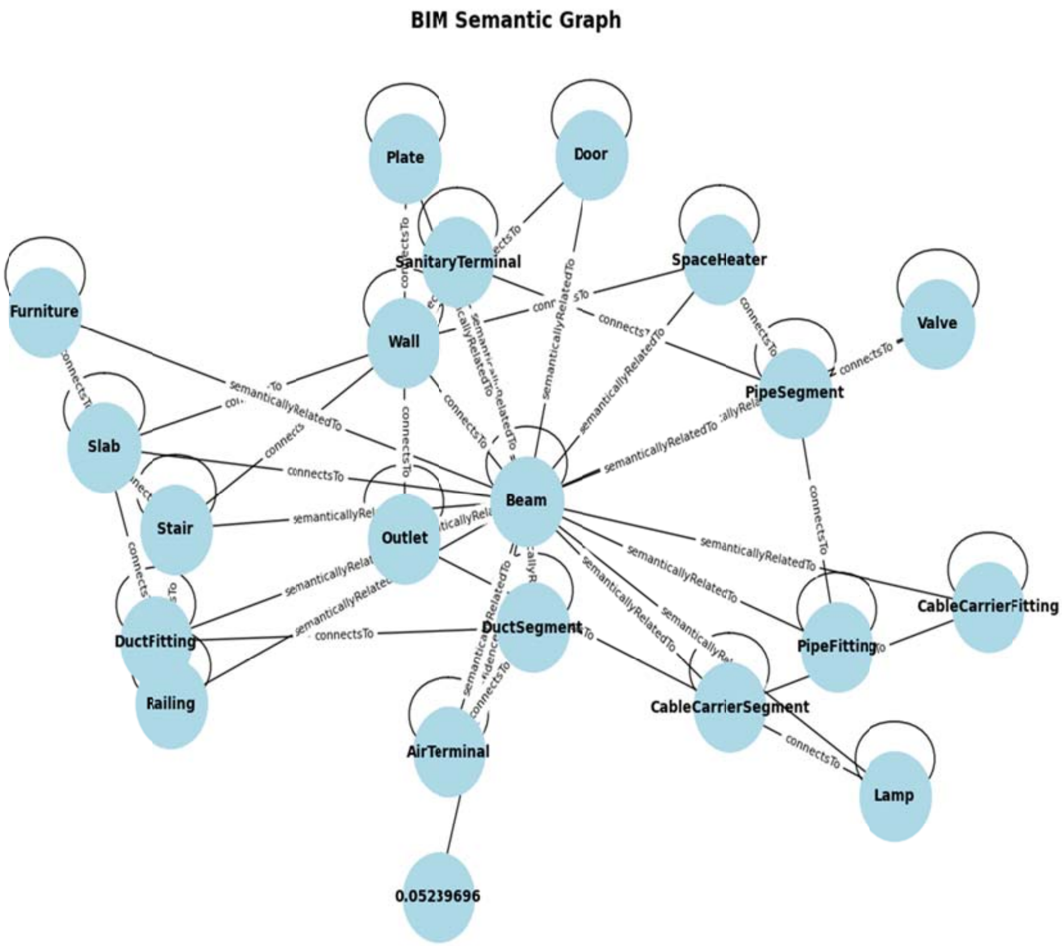

Figure 9 The knowledge graph structure created through the semantic enrichment pipeline

4. Conclusion

Building Information Modeling (BIM) object classification using AI-models is presented. The work adopted two-branch approach to enhance the overall performance of the AI models. Specifically, the two-branch method consists of the geometric feature extraction and relational feature extraction with a feature fusion which are then fed to the BIM object classification model for the final multiclass BIM object classification.

In addition, the work considered semantic enrichment which also depended on the outputs from both the BIM object classification model and the feature fusion model. With the two inputs knowledge graph was created along with semantic database which enables query to be used to elicit the relational information and element's class information from the semantic database. The ideas presented in this work is very essential to enhance collaboration among the various stakeholders always involved in building project lifecycle.

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