Multi-granularity infrastructure-BIM object classification and decomposition for highway project delivery

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Abstract -
Highway project information delivery using building information modelling (BIM) often suffers from inefficiencies when converting 3D Industry Foundation Classes (IFC) models into network representations that conform to agency-specific asset data standards. These inefficiencies primarily arise from inconsistent object classification and mismatches in modelling granularity. To address this challenge, this paper proposes a novel method to automatically classify multi-granularity IFC BIM models and decompose coarse elements into finer components that satisfy asset information exchange requirements. A context-aware mesh neural network (CA-MNN) is developed to incorporate contextual geometric information, enabling more accurate prediction of face-level mesh semantics for IFC elements. Triangulated faces are then grouped based on connectivity, and predictions are smoothed using a majority voting strategy, enabling the decomposition of coarse elements into finer-grained asset models. The proposed method is evaluated using 6,058 IFC elements from real-world highway BIM models in the UK. The results demonstrate that the CA-MNN with smoothing achieves the highest classification accuracy of 86.38%. This study contributes a new BIM object classification and decomposition approach that supports the identification and segmentation of coarse IFC elements for infrastructure project delivery.

Keywords -
Building information modelling (BIM); project information delivery; highway infrastructure management; geometric deep learning

1 Introduction

Highway infrastructure systems comprise roads, bridges, tunnels, traffic signs, drainage, utilities, lighting, and road restraint systems [1]. Effective information delivery is essential for highway construction and reconstruction projects, as reliable asset data strongly influence decisions in subsequent operation and maintenance (O&M) phases. Building information modelling (BIM) technology [2] is widely adopted for information exchange and project data delivery in construction projects. BIM provides semantically rich 3D models representing the geometry and functionality of buildings and civil infrastructure, which can be exchanged across stakeholders and software systems using vendor-neutral Industry Foundation Classes (IFC) specifications [3]. In recent years, BIM-based information delivery has been adopted for infrastructure projects in several countries. For example, Norway has implemented nationwide road project delivery using a common data environment (CDE) platform (Trimble Quadri), where heterogeneous virtual models are uploaded and transformed into IFC-compliant software data models [4]. BIM-based delivery provides more accurate and structured as-built data for operation and maintenance (O&M). Furthermore, when combined with sensing technologies, artificial intelligence, and robotics, infrastructure-BIM (I-BIM) models can evolve into digital twins [5], enabling dynamic asset monitoring and intelligent maintenance decision-making.

Despite this potential, several challenges hinder BIM-based information delivery in highway infrastructure projects. First, there is a mismatch between IFC BIM standards and the asset data standards used by different road agencies [6]. These local asset standards are typically developed around existing asset databases and legacy systems; without clear mappings between data models, contractors have limited incentive to produce well-classified IFC models. Second, the coverage and usability of IFC standards remain limited in the infrastructure domain. For example, a Federal Highway Administration (FHWA) report highlights that road-related IFC entities, such as earthworks, drainage, and ancillary facilities, require further extension to support BIM-based infrastructure management [7]. Third, although recent IFC versions (e.g., IFC 4.3 [3]) introduce broader civil infrastructure concepts, few BIM authoring tools support seamless exchange based on the latest standards; for instance, the highest officially supported IFC export option in Autodesk Revit 2026 remains IFC4 [8]. Consequently, IFC models for highway project delivery are often misclassified or exported using generic types such as *IfcBuildingElementProxy* [9]. In addition, granularity mismatches are common: a single BIM object (e.g., a "deck") may need to be decomposed into multiple asset components (e.g., slabs, pavement, girders) to support downstream asset management, whereas multiple fine-grained objects (e.g., railings) may need to be aggregated into a single asset such as a "pedestrian restraint system."

Previous studies have proposed various technical solutions for automatic BIM object classification using geometric features [10, 9], materials [11], attributes [12], and topological relationships [13, 14]. These approaches generally assume that BIM object instances are already modelled at an appropriate level of granularity and therefore focus on reclassifying objects to assign correct IFC types. However, real-world I-BIM models often exhibit not only typing errors but also inappropriate granularity, where object instances must be either aggregated or decomposed to meet the requirements of hierarchical asset data standards. This shifts BIM object classification from the object level to the part level, requiring finer-grained semantic understanding of 3D models.

To address these challenges, this study proposes an automated method for multi-granularity infrastructure-BIM (I-BIM) object classification and decomposition. The method performs per-face classification of BIM object meshes and decomposes coarse object instances into multiple parts that can be mapped to asset components defined by asset data standards. A context-aware mesh neural network (CA-MNN), built on the MeshNet backbone [15], is developed to incorporate geometric context by selecting K-nearest neighbouring objects and learning both object-level and context-level features to predict semantic labels for each triangulated face. A smoothing and clustering algorithm is then applied to both improve classification and automatically split coarse objects into meaningful parts when multiple asset types are present. The method is evaluated using three types of real-world IFC models, i.e., bridge, culvert, and road, aligned with asset classes defined in the UK Asset Data Management Manual (ADMM) [16]. ADMM provides a tree-structure asset class hierarchy, covering 10 parent asset types (e.g., ancillary, drainage, lighting, pavement), subtypes, and asset components. The best performing model achieves a per-face accuracy of 86.38% on a dataset of 6058 object instances with varying levels of granularity.

The remainder of the paper is structured as follows. Section 2 reviews related work. Section 3 describes the proposed method. Section 4 presents the evaluation results. Section 5 concludes the paper.

2 Literature review

Existing approaches for automatic BIM object classification can be broadly categorized into rule-based methods, machine learning-based methods, and hybrid methods.

Early studies primarily relied on manually defined domain-specific rules. Belsky et al. [17] developed a semantic enrichment engine for BIM (SeeBIM) that enables the composition of inference rule sets based on properties, geometry, topology, and functional relationships. Sacks et al. [13] further extended the SeeBIM engine with additional operators to classify BIM models of highway bridges. Ma et al. [14] developed matching algorithms for object identification by incorporating domain knowledge of shape features (e.g., orientation, volume) and pairwise relationships. Wu and Zhang [10] proposed an algorithm for classifying structural objects using inherent geometric features, such as the number of subcomponents, number of faces, and cross-sectional profiles.

Rule-based methods tend to be rigid and difficult to scale across diverse object types and features. Consequently, machine learning- and deep learning-based approaches have been increasingly explored. Wu et al. [18] proposed invariant signatures based on geometric and material features to describe IFC entities and evaluated classification performance using five machine learning models (e.g., random forest). Kim et al. [19] proposed an approach for automatically classifying building object instances in BIM models using a 2D convolutional neural network (CNN). Koo et al. [9] applied two geometric deep learning models, i.e., multi-view CNN and PointNet [20], to classify I-BIM objects such as culverts, retaining walls, and wing walls, and further extended this work to classify subtypes of BIM elements for walls and doors. Collins et al. [21] developed a graph convolutional network-based approach that operates on native triangle meshes and automatically generated local features for BIM object classification. Emunds et al. [22] proposed SpaRSE-BIM, a neural network based on sparse convolutions for classifying IFC-based geometry. Wang et al. [23] applied graph neural networks for room type classification and semantic enrichment of BIM models. More recently, Teclaw et al. [24] proposed Context-NET, which integrates contextual information from surrounding components by incorporating spatial relationships to improve object classification performance.

Recent studies have also explored hybrid approaches that integrate multiple types of features to improve classification accuracy. Utkucu et al. [25] applied an ensemble framework using a stacking strategy that combines four BIM classification tools: keyword search, rule-based inference, machine learning based on geometric features, and deep learning based on visual shape features. Luo et al. [26] introduced a two-branch geometric–relational deep learning framework that fuses geometric and relational features for IFC element classification. Yang et al. [27] proposed IFCGeoNet, which integrates explicit shape features and implicit representation features through graph learning. Similarly, Han et al. [28] and Wang and Ying

[29] developed generic graph neural network-based frameworks that embed semantic, spatial, and topological features of BIM models, where BIM element classification is treated as one of the downstream tasks.

In summary, existing context-aware methods (e.g., Context-NET) perform object-wise classification, where each IFC element in a BIM model is treated as an independent instance. However, they do not address granularity mismatch issues commonly observed in BIM-enabled infrastructure project delivery, where coarse IFC elements should be decomposed and overly fine-grained elements should be aggregated. Addressing this challenge requires hierarchy-aware classification and part-level semantic segmentation of infrastructure-BIM (I-BIM) objects.

3 Proposed solution

3.1 Overview

In this study, we propose a CA-MNN-based approach to automatically classify I-BIM object instances while enabling the decomposition of coarse elements. Figure 1 presents an overview of the proposed framework. The method begins with preprocessing I-BIM models exported from IFC-authoring software. The geometry is tessellated into triangulated meshes composed of vertices and faces. Quadric edge collapse is then applied to obtain decimated meshes that preserve the core geometry. The decimated mesh of each object instance is stored together with its GUID, which serves as a reference for generating contextual geometry.

For each object instance in an IFC model, the goal of CA-MNN is to predict the class types of all triangulated faces. The class types are derived from asset data standards used by highway agencies. In this study, three types of I-BIM models (i.e., bridge, culvert, and road) are used, covering a total of 30 asset classes defined in ADMM (see Table 2). The predicted face semantics are used to determine (a) the type of the IFC element and (b) whether its modelling granularity is too coarse and therefore requires decomposition. If an IFC element contains faces belonging to different asset classes, it is segmented into multiple parts by clustering faces of the same class.

The CA-MNN pipeline consists of three steps (see Figure 1). First, the K-nearest IFC elements surrounding the target element are retrieved. The decimated meshes of these neighbouring elements are combined as contextual faces until a maximum size is reached to satisfy memory constraints. Using decimated meshes instead of raw meshes allows more contextual elements to be incorporated. Second, a mesh neural network architecture is designed to embed both target geometry and contextual geometry into dense feature descriptors. The contextual feature descriptor is concatenated with the feature vectors of each triangulated face of the target element. A multilayer perceptron (MLP) then outputs class scores for each asset type. Third, connected faces are grouped and overlapping groups are merged. A final class is assigned to each group using majority voting, where the most frequent predicted class within a cluster is selected.

Based on these three steps, IFC object instances are classified and coarse elements are decomposed into parts with appropriate granularity according to asset data standards. The processed IFC models can then be seamlessly exchanged with infrastructure asset management systems (AMS). The following subsection details the architecture of CA-MNN.

3.2 Context-aware mesh neural network

The architecture of CA-MNN is illustrated in Figure 2. The network extends the original MeshNet [15] backbone with (a) a lightweight context branch and (b) a face-wise classifier. The inputs consist of meshes for both the target element and its surrounding context: the target geometry contains F_t faces, while the context mesh provides up to F_c faces. Each face includes a center point, three corner points, one normal vector, and neighbourhood indices.

The target mesh and context mesh are processed independently through the same descriptor modules and mesh convolution pipeline. First, center vectors ($n \times 3$), where n denotes the number of faces, are processed by a spatial descriptor, implemented as a multilayer perceptron (MLP) that embeds spatial features into a 64-dimensional vector. In parallel, corner points and normal vectors are processed by a structural descriptor that captures shape features. In the MeshNet [15] backbone, two types of structural descriptors are used. The first performs face rotation convolution over corner vectors to capture intra-face structural features. The second applies face kernel correlation, which uses normal vectors of each face and its neighbours to encode local geometric affinities.

In both branches, spatial and structural features are passed to two mesh convolution layers to expand the receptive fields of faces by aggregating information from neighbouring faces. The mesh convolution layer includes two parts. The first part combines spatial and structural features and applies a MLP to generate 512-dimensional global features. The second part aggregates the structural features of a face with those of connected faces through vector concatenation.

After two mesh convolution layers, spatial and structural features are concatenated in each branch, respectively. Regarding target branch, we apply an MLP to generate feature vectors for all faces ($F_t \times 1024$). In terms of context branch, we employ an adaptive average pooling layer that collapses the variable-length face dimension to size of 1, meaning that per-face features are transformed into a

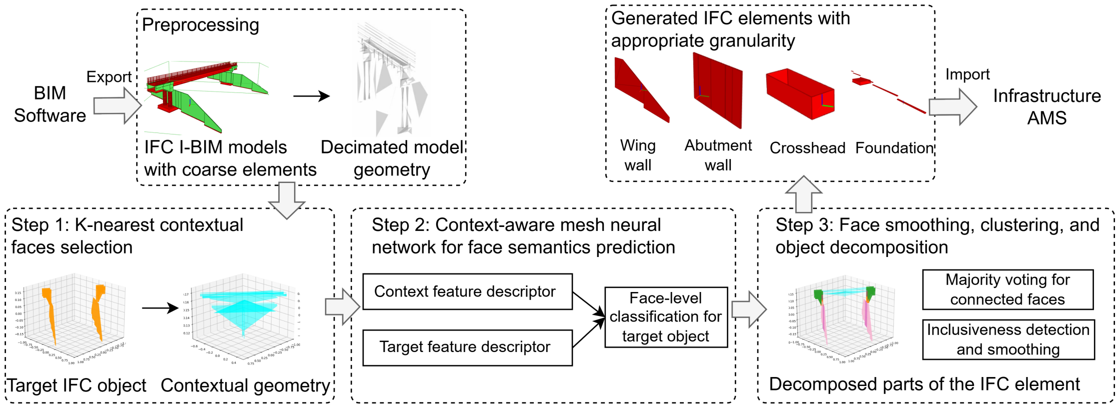

Figure 1. Overview of the proposed CA-MNN-based approach for granularity-aware I-BIM object classification and decomposition.

global feature of context geometry. Further, we use one MLP to generate a 256-dimensional vector, which is concatenated with per-face feature of target geometry ($F_t \times (1024{+}256)$). Finally, we exploit a 1d convolutional layer to output final scores($F_t \times$num_classes) for face-level classification, where num_classes represents the total number of asset class types.

4 Performance evaluation

4.1 Experiment design

We evaluate the proposed method using real-world BIM models from UK highway projects. The dataset includes five bridge models, five culvert models, and five road models, covering 30 asset classes defined in ADMM. All IFC models were imported into Blender for manual annotation. Specifically, ground-truth labels were assigned to each IFC element in the I-BIM models. For coarse IFC elements containing multiple asset units, Blender tools were used to split the geometry and generate finer IFC elements with corresponding ADMM labels. The dataset was further expanded by synthesizing coarse IFC elements through recombination of real elements from the original models. The generation process follows the statistical distribution of element types and group sizes observed in the original dataset, while applying controlled sampling to balance the occurrence of different object classes. Semantic consistency is preserved via asset hierarchy constraints, and duplicate combinations are eliminated based on source element IDs to ensure the uniqueness of all samples.

The final evaluation dataset contains 6,058 IFC elements, including 5,376 coarse elements requiring decomposition. The proportion between synthetic and original samples is 51:1. The class distribution is illustrated in Figure 3. The dataset was split into training and test sets using an 8:2 ratio, resulting in 4,845 training samples and 1,213 test samples.

The CA-MNN model was trained using the training set. The maximum numbers of target faces and context faces were set to 30,000 and 10,000, respectively. The batch size was set to 2, and the model was trained for a fixed number of 100 epochs to ensure sufficient convergence during training. Convergence is evidenced by the stabilisation of the training loss, where the relative decrease in loss is less than 1% over 10 consecutive epochs, occurring around the 90th epoch. The final model obtained after 100 epochs was used for evaluation on the test set.

4.2 Test results

We evaluate the proposed method using face-level classification accuracy. As shown in Table 1, CA-MNN correctly classifies 8,919,146 faces out of 10,325,920, achieving an accuracy of 80.80%. After applying the face smoothing operation, the accuracy increases significantly to 86.38%, demonstrating the effectiveness of smoothing and clustering connected faces to eliminate local misclassifications caused by ambiguous geometric features. However, although connectivity-based smoothing improves overall performance, it may introduce additional errors for tightly connected components such as abutment walls and wing walls.

In comparison, the mesh neural network without the context branch achieves an accuracy of 74.68%, which increases to 80.0% after smoothing. The performance gap indicates that the context branch in CA-MNN effectively incorporates surrounding information for better understanding of IFC geometry semantics and granularity.

Per-class classification performance is reported in Table 2. The macro-average accuracy across classes is 77.65%, indicating that performance is influenced by the imbalanced distribution of face counts across classes, which stems from disparate mesh complexity. Major

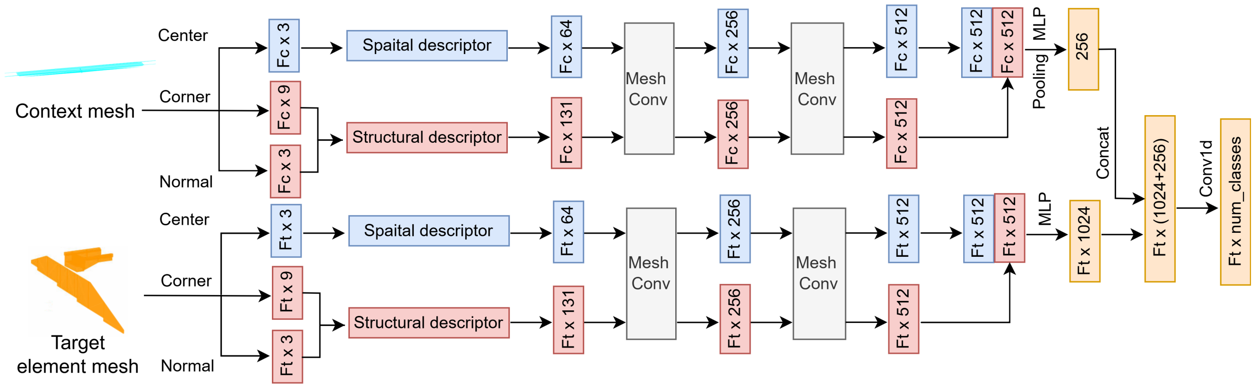

Figure 2. The architecture framework of the context-aware mesh neural network for face-level IFC geometry classification.

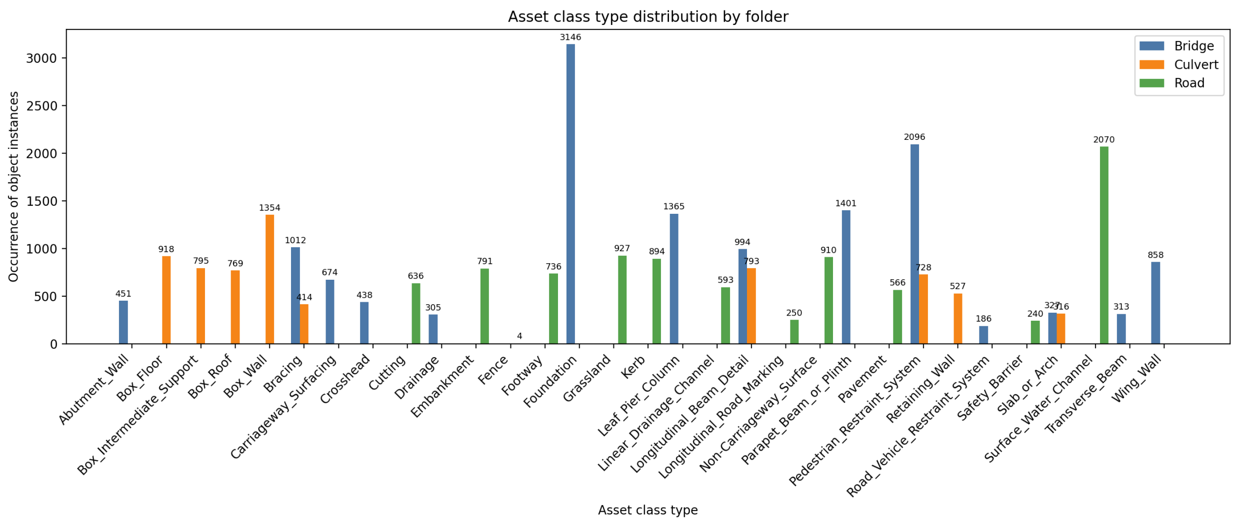

Figure 3. The distribution of different asset class types in the dataset.

classes with more faces generally achieve accuracies above 90%, whereas minority classes perform worse. For example, the accuracy for abutment walls (428 faces) is only 44.9%. Accuracy rates for bridge, culvert, and road models are 82.05%, 89.18%, and 78.84%, respectively, indicating reasonably balanced performance across infrastructure types.

Classification errors arise from several factors. First, CA-MNN struggles with geometrically featureless object types such as carriageways, footways, and safety barriers, which are often represented as simple cuboids. Table 2 shows consistently lower accuracy for these classes, and they are frequently misclassified as one another. For example, safety barriers are most often misclassified as linear drainage systems (16.6%). These errors typically occur across the entire element, indicating that CA-MNN fails to correctly interpret the object as a whole. Incorporating additional features, such as colour for recognising road markings, could be beneficial. However, as noted by Sacks et al. [13], semantic enrichment methods should ideally function under the worst-case scenario where only geometry is available, and the integration of additional features depends on the quality of the input BIM models. Second, the imbalanced distribution of mesh quantities across classes reduces performance on minority classes. Third, the current context extraction strategy may retrieve surrounding objects with large mesh sizes, which can dilute the representation of global contextual information. In addition, K-nearest neighbour retrieval is based on distance to the centroid of the target object, which is suboptimal for objects consisting of spatially separated components, such as groups of bridge foundations.

In terms of part decomposition performance, the mIoU achieves 0.701 across the entire test set and 0.667 for

Table 1. Model performance comparison

Model	Correct faces	Accuracy (%)
CA-MNN + smoothing	8919146	86.38
CA-MNN	8343047	80.80
MNN + smoothing	7692810	79.20
MNN	8178128	74.50

coarse IFC elements that contain multiple classes. In comparison, the overall mIoU drops to 0.603 without smoothing operation.

5 Conclusion

BIM-based highway information delivery faces challenges in aligning IFC models with agency-specific asset data standards, particularly due to granularity mismatches between construction and operation requirements. This often leads to labour-intensive manual processing in BIM or CDE platforms. To address this, this paper proposes a mesh neural network-based method for automatic classification of multi-granular infrastructure-BIM (I-BIM) objects, where coarse elements are identified and decomposed into finer components that better satisfy asset data requirements.

The proposed geometric deep learning (GDL)-based approach begins by tessellating IFC models into triangulated meshes, followed by geometry decimation using quadric edge collapse. The inference process of CA-MNN consists of three steps. First, the K-nearest surrounding objects of a target element are retrieved to form the contextual mesh. Second, the CA-MNN processes both target and contextual meshes through dual network branches to capture spatial and structural features, respectively. The global context feature is then concatenated with per-face features of the target object to perform face-level classification. Third, connectivity-based smoothing and clustering are applied to group faces with the same class labels, enabling both classification of IFC elements and decomposition of coarse elements into finer parts for downstream integration with infrastructure AMS.

The proposed approach is evaluated using 6,058 IFC elements from real-world BIM models, covering 30 asset classes defined in the Asset Data Management Manual (ADMM) used in the UK highway industry. The results show that CA-MNN with smoothing correctly classifies 8919146 faces out of 10325920, achieving an accuracy of 86.38%. Without smoothing, the accuracy decreases to 80.80%. We further evaluate a mesh neural network without the context branch, where accuracy drops to 79.20% with smoothing and 74.50% without smoothing. These results demonstrate the effectiveness of incorporating contextual geometry into GDL models for capturing semantic and topological relationships among infrastructure elements.

The contributions of this study are twofold. First, we propose a novel pipeline for automatic classification of multi-granular I-BIM objects using face-level semantics, which enables coarse IFC elements to be decomposed into parts with suitable granularity. Second, by combining geometry decimation, K-nearest context selection, and a dual-branch CA-MNN architecture, the method effectively learns contextual geometry and improves classification accuracy, as confirmed by the experimental results.

This study also has some limitations. First, CA-MNN struggles to reliably recognise elements with featureless geometry, such as roadways. Second, model training is negatively affected by class imbalance, leading to poorer performance on minority classes. Third, the current context selection strategy may retrieve irrelevant surrounding geometry. Future work will focus on improving context selection strategies and mesh neural network architectures to further enhance performance. In addition, a comprehensive AI-assisted workflow will be developed to support fully automated BIM-based information delivery for highway projects.

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Table 2. Per-class face accuracy

Asset class	Face numbers (Correct/Total)	Accuracy (%)
Leaf_Pier_Column	94879 / 96692	98.10
Foundation	8629 / 8862	97.40
Crosshead	1330 / 1763	75.40
Pedestrian_Restraint_System	995093 / 1112537	89.40
Parapet_Beam_or_Plinth	108739 / 119893	90.70
Slab_or_Arch	21421 / 23113	92.70
Longitudinal_Beam_Detail	133677 / 164546	81.20
Carriageway_Surfacing	117051 / 201155	58.20
Bracing	31278 / 31604	99.00
Drainage	60519 / 107115	56.50
Transverse_Beam	8744 / 10741	81.40
Road_Vehicle_Restraint_System	127039 / 128017	99.20
Abutment_Wall	192 / 428	44.90
Wing_Wall	2236 / 2865	78.00
Box_Intermediate_Support	10151 / 10290	98.60
Box_Roof	2453 / 2552	96.10
Box_Wall	24433 / 24630	99.20
Box_Floor	9641 / 9748	98.90
Retaining_Wall	87891 / 101671	86.40
Embankment	169556 / 262089	64.70
Cutting	167176 / 230291	72.60
Surface_Water_Channel	1181163 / 1210525	97.60
Linear_Drainage_Channel	24343 / 31277	77.80
Footway	126153 / 136696	92.30
Non-Carriageway_Surface	163343 / 231190	70.70
Kerb	104775 / 106488	98.40
Longitudinal_Road_Marking	113190 / 242742	46.60
Safety_Barrier	41743 / 128411	32.50
Pavement	156934 / 285642	54.90

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