BIM, machine learning and computer vision techniques in underground construction: current status and future perspectives

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Abstract

The architecture, engineering and construction (AEC) industry is experiencing a technological revolution driven by booming digitisation and automation. Advances in research fields of information technology and computer science, such as building information modelling (BIM), machine learning and computer vision have attracted growing attention owing to their useful applications. At the same time, population-driven underground development has been accelerated with digital transformation as a strategic imperative. Urban underground infrastructures are valuable assets and thus demanding effective planning, construction and maintenance. While enabling greater visibility and reliability into the processes and subsystems of underground construction, applications of BIM, machine learning and computer vision in underground construction represent different sets of opportunities and challenges from their use in above-ground construction. Therefore, this paper aims to present the state-of-the-art development and future trends of BIM, machine learning, computer vision and their related technologies in facilitating the digital transition of tunnelling and underground construction. Section 1 presents the global demand for adopting these technologies. Section 2 introduces the related terminologies, standardisations and fundamentals. Section 3 reviews BIM in traditional and mechanised tunnelling and highlights the importance of integrating 3D geological modelling and geographic information system (GIS) databases with BIM. Section 4 examines the key applications of machine learning and computer vision at different stages of underground construction. Section 5 discusses the challenges and perspectives of existing research on leveraging these emerging technologies for escalating digitisation, automation and information integration throughout underground project lifecycle. Section 6 summarises the current state of development, identified gaps and future directions.

Keywords: Building information modelling; computer vision; machine learning; tunnelling; underground construction

1. Introduction

Two decades have elapsed since entering the 21st century, and driven by the prevalence of digitisation and massive data generation, the AEC industry is experiencing tremendous changes. In this transition, a collaborative use of technologies plays a vital role in meeting the needs of creating products, processes and systems that are interconnected, controllable and essentially, 'smart'. Underground infrastructure has attracted growing attention in providing an extra dimension of space under rapid urbanisation. With almost every construction-related process being heavily influenced by the wave of digitisation, underground construction is no exception.

The possibility of digital delivery of mega-scale subsurface infrastructure through leveraging advanced computing and data storage solutions has been exemplified by a number of high-profile projects, such as the London Crossrail in UK (Crossrail Limited, 2017), the MRT Line 2 (SSP) underground works in Malaysia (MRT Corp, 2020), and the Badaling station of Beijing-Zhangjiakou high-speed railway in China (AREP, 2020). The transformation efforts within underground construction towards digital solutions are mainly driven by two reasons. On the one hand, the rapid urbanisation accompanied by a growing population stimulates the utilisation of underground space and tunnelling (National Research Council, 2013; United Nations, 2019). For example, as of 2019, Beijing has over 21 million long-term residents and covered an area of 16,410 square kilometres. To serve its residents, the city has built one of the most extensive metro systems in the world consisted of 391 stations and 22 lines with a total length of 637 km (BTDRC China, 2019). On the other hand, the maintenance burden of existing underground projects is greatly increased due to lacking a management platform supporting visualisation and information updates regarding their locations and status. London owns one of the world's oldest metro systems accompanied with laid utility networks intertwining with each other. The cost of accidental strikes on underground pipes and cables can reach 1.2 billion British pounds a year (Geospatial Commission UK, 2019). To help mitigate the issue and remove workers from the danger of accidentally striking gas or electric pipes, the UK government's Geospatial Commission is creating the Underground Asset Register that provides a digital map of underground pipes and cables to enable more efficient access, utilisation and sharing of data of buried assets (Geospatial Commission UK, 2019). A similar approach is undertaken by the Singapore-ETH Centre in collaboration with the Singapore Land Authority to create a digital twin of the underground of Singapore harnessing 3D technology (Schrotter and van Son, 2019) in line with its national plan that values the effective use of underground space as a core strategy (URA Singapore, 2019).

The above has indeed revealed the demand for adopting digital information technologies to reinforce efficient and effective planning, development and management of underground construction. There has been increasing interest of the AEC industry in using BIM to stimulate multifaceted transitions in aspects of facility design, construction management and stakeholder collaboration (Borrmann et al., 2018; Sacks et al., 2018). The technology, underpinned by advanced ICTs, promotes efficient management of highly complex and dynamic information flow throughout a project's lifecycle while supporting the communication and collaboration among participants (Borrmann et al., 2018; Bradley et al., 2016; Cerovsek, 2011; Eastman et al., 2008, 2011; Sacks et al., 2018; Volk et al., 2014). While presenting manifold opportunities, digital transformation in urban underground development is facing unique challenges caused by the intrinsic complexity associated with spatial opaqueness, geological uncertainties, high-risk working environment and ground-machine-structure interactions. Excavation carried out without a reasonable understanding of the ground features can be especially problematic. A project-scale geological understanding established incorporating the GIS databases, geological observation and geophysical investigation is essential to mitigate the uncertainties inherited from the ground. Therefore, modelling with close reference to geographical and geological information is an important strategy for BIM in underground construction. The accuracy of the federated BIM model is to be continuously enhanced with domain-specific knowledge reconciled with as-built and as-damaged information.

BIM, big data and robotics, envisioned as key technologies in the context of Industry 4.0 for the construction industry (Oesterreich and Teuteberg, 2016; Rüßmann et al., 2015), demonstrate conceivable benefits in the digital transformation process of underground construction. The focuses on the collective capabilities of data acquisition, processing and management have reached an unprecedented level as dependence on intelligent technologies, and smart devices continue to increase. Acquiring data from prospecting and mapping, machine and structural monitoring, with robots introduced on top of traditional tools is merging into a trend. The volume, velocity and variety of the generated data have exceeded the ability demonstrated by any traditional data analysis method. Machine learning and computer vision techniques represent huge potential for big data analysis by seizing the opportunities in the growth of data and computer processing power. There have been wide applications developed based on machine learning and computer vision for reflecting the evolving state of construction and its surrounding environment (Brilakis and Haas, 2019; Darko et al., 2020; Ibrahim et al., 2020; Koch et al., 2015; Spencer et al., 2019; Xie et al., 2020; Zhu et al., 2020). The data-driven solutions integrated with model-based approaches form a new direction for the lifecycle management of infrastructure. The mechanism of implementing data that reflects the prevailing circumstances of a physical system into its virtual replica shares some similarities with the concepts of a digital twin and cyber-physical system (CPS) (Anumba and Roofigari-Esfahan, 2020; NSF, 2020; Shafto et al., 2012; Wu and Fang, 2020).

This paper aims to provide a critical review of integrating BIM, machine learning, and computer vision into mechanised tunnelling and underground stations from the perspectives of geotechnical engineering and structural integrity assessment. A systematic literature survey was conducted to identify the research trends concerning BIM, machine learning, and computer vision within underground construction. Four databases are chosen for the paper retrieval, namely Scopus, Web of Science, American Society of Civil Engineers (ASCE) Library, and IEEE Xplore Digital Library, among which Scopus is the core collection. Search results are then selectively reviewed based on refining topics to concentrate on tunnel and underground station/space. For example, there are a total of 388 publications refined from Scopus (from 2010 to 1 June 2020) showing a very rapid growth in these topics, particularly since 2015 (Figure 1). The paper is to demonstrate the demand and provide a logical foundation in these topics rather than to conduct the bibliometric analysis.

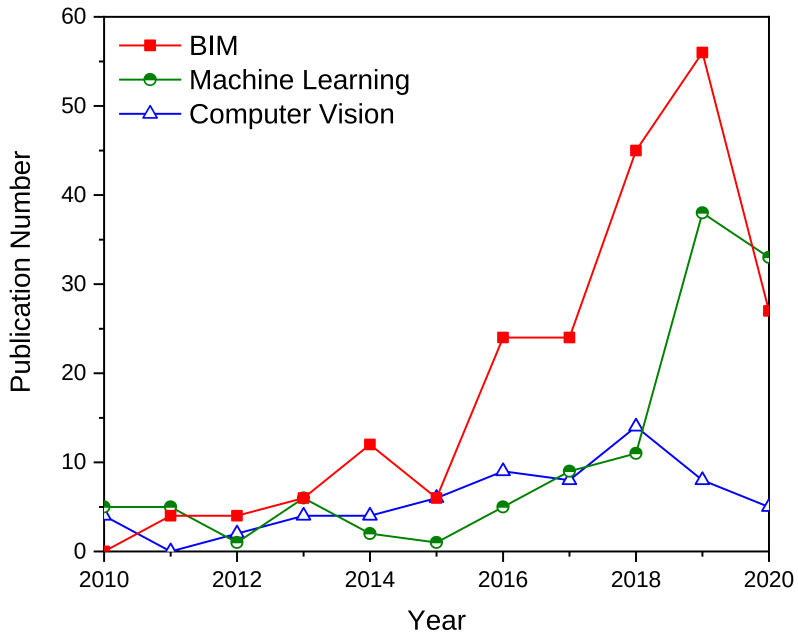


Figure 1 Publication frequency from 2010 to 2020 (data accessed from Scopus on 01/06/2020): Three query strings were created in Scopus as 1) TITLE-ABS-KEY ("building information model*" OR BIM) AND TITLE-ABS-KEY (tunnel* OR underground); 2) TITLE-ABS-KEY ("machine learning") AND TITLE-ABS-KEY (tunnel* OR underground); and 3) TITLE-ABS-KEY ("computer vision") AND TITLE-ABS-KEY (tunnel* OR underground).

This paper is organised as follows. Section 2 introduces the domain-specific terminologies and fundamentals. Section 3 briefly reviews 3D geological modelling and GIS, and examines the state-of-the-art development of BIM for tunnelling and underground construction. Section 4 evaluates the trends and applications of machine learning and computer vision techniques in underground prospecting, inspection and monitoring. Section 5 provides a general discussion on the subject directions, highlighting the collaboration opportunities of BIM, machine learning and computer vision at different stages of underground construction. Section 6 concludes this paper by summarising the current state of development, identified gaps and future directions.

2. Terminologies and fundamentals

In recent years, the trend of digitisation and automation has been envisioned as popular terms within the construction industry. Oesterreich and Teuteberg (2016) built a concept list by grouping the main technologies and terms in the context of Industry 4.0, as detailed in Table 1. CPS is “engineered systems that are built from, and depend upon, the seamless integration of computation and physical components” (NSF, 2020). Product-Lifecycle-Management (PLM) and BIM share some fundamental similarities, but BIM is believed to represent a paradigm shift regarding lifecycle processes and management in the AEC industry.

Table 1 Concept list of technologies in the construction industry. Reproduced from (Oesterreich and Teuteberg, 2016)

Cluster	Key technologies in the context of Industry 4.0	Sections in this paper
Smart Factory	Cyber-Physical Systems (CPS)/Embedded systems	3.4, 3.5, 5.2
	Internet of Things (IoT) /Services (IoS)	
	Automation	5.4
	Modularisation/Prefabrication	3.6
	Additive Manufacturing	
	Product-Lifecycle-Management (PLM)	2.1, 3, 5.1, 5.2, 5.3
	Robotics	5.4
	Human-Computer Interaction (HCI)	
Simulation and modelling	Building Information Modelling	2.1, 3, 5.1, 5.2, 5.3
	Simulation tools/Simulation models	3.4, 5.3
	Augmented Reality (AR)/Virtual Reality (VR)	5.2, 5.3
Digitisation and virtualisation	Cloud Computing	
	Big Data	4
	Mobile Computing	
	Social Media	
	Digitisation	3, 4

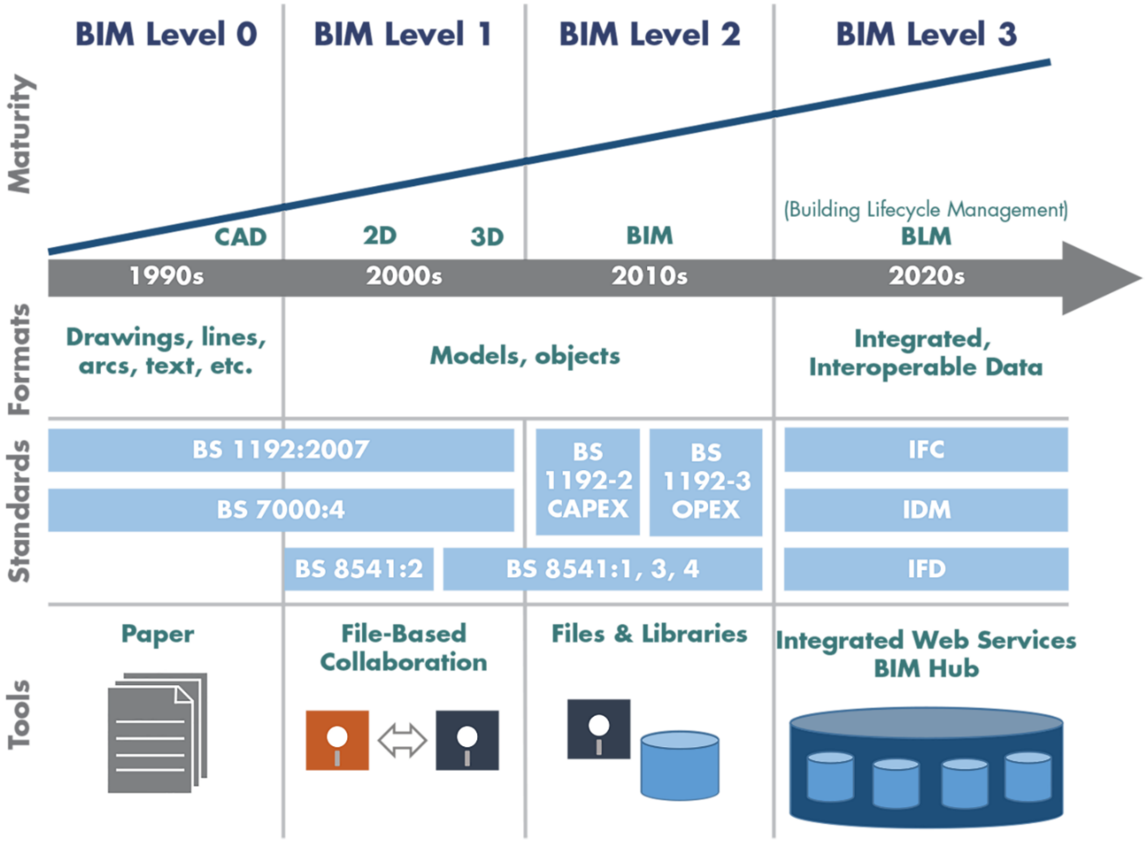
2.1 Definition and standardisation of BIM

The definition of BIM varies in different contexts and from different standpoints (Barlish and Sullivan, 2012). A commonly accepted definition provided by the US National Building Information Modelling Standard (NBIMS-US™) states that BIM is

"*a digital representation of physical and functional characteristics of a facility. A BIM is a shared knowledge resource for information about a facility forming a reliable basis for decisions during its lifecycle; defined as existing from earliest conception to demolition.*" (NIBS, 2015).

Other definitions acknowledged widely are those given by British Standards Institution (BSI) and International Standards Organisation (ISO), such as the BS EN ISO 19650-2: 2018 defines BIM as "the process of designing, constructing or operating a building or infrastructure asset using electronic object-oriented information" (ISO, 2018) and ISO 29480-1:2016 as "use of a shared digital representation of a built object (including buildings, bridges, roads, process plants, etc.) to facilitate design, construction and operation processes to form a reliable basis for decisions." (ISO, 2016). An in-depth introduction to BIM from both practical and technological perspective can be found in these classical textbooks (Borrmann et al., 2018; Eastman et al., 2008, 2011; Sacks et al., 2018).

The concept of "BIM maturity levels" derived from the BIM maturity model (Figure 2a) is accepted by the UK Government BIM TASK Group (Sacks et al., 2018). From Level 0 to Level 3, the degree of collaboration improves as the application level of information technology in construction matures. It progresses from Level 0: unstructured computer-aided design (CAD) and paper-based data communication over to Level 1: electronic sharing of both 2D and 3D data engaging a common data environment (CDE), and moving up to Level 2 (mandatory BIM level in the UK on all government construction projects): collaborative working via a federated BIM model before finally reaching Level 3: a full collaboration between all disciplines working via a single, shared project model that is held in a centralized repository. The PAS 1192 standards that adopt "BIM maturity levels" are now superseded by BS EN ISO 19650 -1 &2:2018 (BSI, 2020a, b), which specify the requirements on the organisation and digitisation of information about buildings and civil engineering works using BIM. Based on BS EN ISO 19650-1, the information management maturity is developed in a sequence of stages, as shown in Figure 2b (BSI, 2018). As the maturity climbs, business benefits increase with the development of standards, advanced technology and more comprehensive information management approaches.



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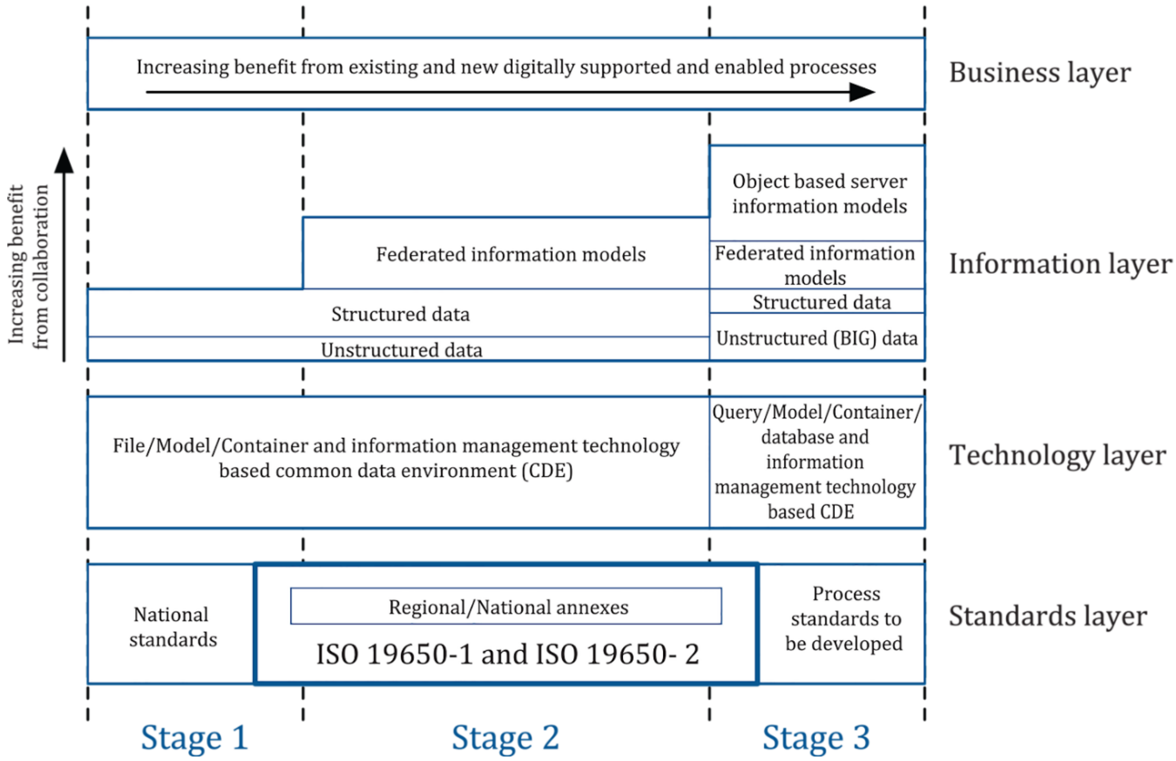


(b)

Figure 2 (a) BIM maturity levels, reproduced from (Sacks et al., 2018), (b) a perspective on stages of maturity of analogue and digital information, reproduced from (BSI, 2018).

BIM can be differentiated into "Closed BIM" and "Open BIM" that are distinguished by the implementation of open, neutral data exchange formats (Borrmann et al., 2018). The common understanding of the language used in the product model is becoming increasingly important to ensure the consistency of information exchanged and to facilitate the multidisciplinary collaboration in major infrastructure projects. The semantic enrichment and consensus can be achieved by forming structured vocabularies and classification systems that contain multiple languages to define terminologies and relationships between them. "buildingSMART Data Dictionary" (bSDD) created by buildingSMART International (bSI) is such a glossary or a shared library of objects and their attributes using ISO 12006-3 ontology for the building and construction industry (bSI, 2019a).

The Semantic Web built upon the World Wide Web intends to bring structure to the web contents and allow query of data, i.e. enable machines to process the data by "understanding" them (Antoniou et al., 2012). Leveraging metadata models such as the Resource Description Framework and ontologies that are specifications of conceptualisations, Semantic Web technology integrated with BIM will help enhance information retrieval capacity by data query and data-driven reasoning to facilitate better collaboration between project participants (Underwood and Isikdag, 2011). Karan et al. (2016) discussed the integration and interoperability of BIM and GIS based on the Semantic Web. A review on BIM integration to Semantic Web technology is given by Godager (2018).

2.1.1 Parametric geometry modelling

From a historical perspective, BIM model generation and design technology are evolved and matured based on 3D solid modelling, which represents the ability to generate and revise arbitrary 3D solid, and eventually object-oriented parametric geometry modelling. The state-of-the-art method integrated two forms of 3D solid modelling techniques, namely the boundary representation (Brep) and the Constructive Solid Geometry (CSG), to realise functions of editing, visualising, measuring, clash detection as well as other non-editing uses (Sacks et al., 2018). Thereafter, the solid modelling CAD systems were improved by recognising the connectivity of shapes through sharing parameters and building links. Based on the degree of intelligence embedded in the parametric model, the modern parametric modelling system is classified into: (1) parametric solid modelling that is the simplest form of parametric modelling by defining the complex shapes or assemblies using a few parameters; (2) parametric assembly modelling that allows the creation of assemblies of individual parametric objects by instantiating such objects and specifying parametric relations between them; and (3) parametric model composed of topology-based parametric objects or script-based rules (Sacks et al., 2018).

BIM applications and BIM-enabled platforms usually provide an extensive set of predefined parametric object classes and families while allowing users to customise, when a desired parametric object does not exist in the specific BIM tool. However, the target functionality of most BIM tools designed for architectural and building modelling is not well suited for the infrastructure projects, constructing custom parametric objects and families becomes inevitable. The fulfilment of parametric modelling under this circumstance is often challenged by the integration of the custom objects with the system rules and specifications embedded in the BIM platform.

2.1.2 IFC data exchange

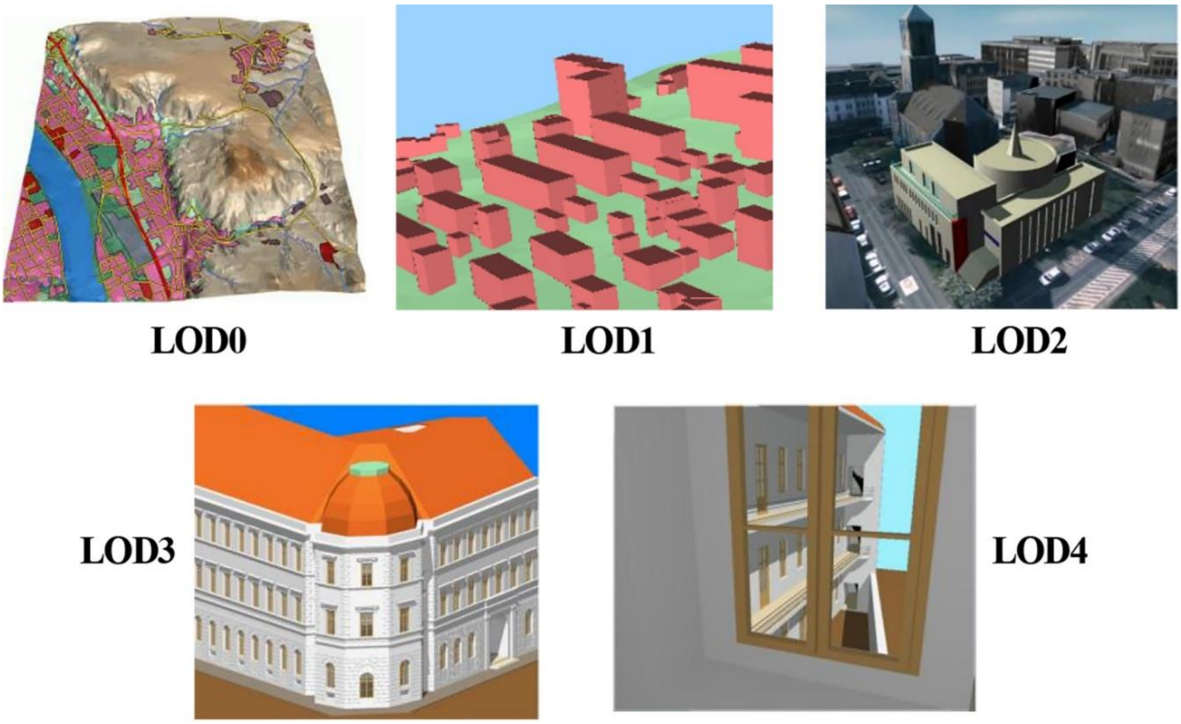
Facilitating interoperability of data exchange between different software is a fundamental challenge for incorporating BIM technology into AEC activities. As aforementioned, to enhance the interoperability involving multiple applications handled by multiple stakeholders (Steel et al., 2012), ISO-STEP (Standard for the Exchange of Product model data, ISO 10303) endeavoured to develop standardised data models or schemas for a level exchange of product and object model (Sacks et al., 2018). In the domain of buildings, Industry Foundation Classes (IFC) as one of the main product data models developed in the course of time by buildingSMART became International Standard (ISO 16739) in 2013. Except for LandXML that has been well established for representing objects of roads, the infrastructure domain has longed for adequate data schemas to perform exchange of data containing infrastructure objects.

Before examining IFC as a data schema specified for BIM data representation and exchange, it is important to understand the contents that need to be transferred between applications while maintaining meaning. For different application domains, distinct subsets of information are required in order to meet with specific utilisation objectives and standards (Lee et al., 2015). The full capture of data requirements will involve knowledge input from experts in their respective domains; the requirements are then specified in the so-called "information delivery manuals (IDMs)" (Eastman et al., 2010). Considering the entities available in the IFC schema are more extensive than needed in any given exchange, specific task-oriented exchanges, referred to as model views, by employing subsets of IFC schema are required. An optimal exchange, in terms of geometric correctness and semantic completeness, of a BIM model using IFC is only achievable given these classes are clearly defined and adequately incorporated in the model. To this end, model view definitions (MVDs) are prepared with information requirement specified to assist software developers in creating export and import translators for delivering and receiving the IFC subsets (Eastman et al., 2010).

2.1.3 Integrated solutions of BIM and GIS

GIS is a computer-based system that handles georeferenced data through data capture and preparation, data management, including storage and maintenance, data manipulation and analysis, and data presentation (Huisman and By, 2009). Therefore, BIM and GIS are both associated with information repository and data management, with BIM characterised by detail-oriented information encompassment, and GIS focusing on manipulative management of geospatial data. System management can greatly benefit from coupling the life-cycle information management capacity provided by BIM with the locational clarity provided by GIS. The integrated applications of GIS and BIM have expanded into the AEC industry (Song et al., 2017; Wang et al., 2019a; Zhang et al., 2009), expecting to maximise the efficiency and accuracy of a project's decision-making process by concurrently employing the strengths of the two domains. Examples of applying BIM-GIS integrated solutions include visualising supply chain management (Irizarry et al., 2013), flood damage to the building (Amirebrahimi et al., 2015), and sustainable built environment (Wang et al., 2019a), as well as utility information management (Cheng and Deng, 2015; Lee et al., 2018; Liu and Issa, 2012).

Open Geospatial Consortium (OGC) is an international community committed to advancing the development and implementation of open standards for geospatial location information and services. The standard data model and exchange format developed by OGC for representation and exchange of 3D city models is CityGML (Kolbe et al., 2005). Levels of detail (LoD) is one of the general concepts associated with CityGML and an important notion to consider in the attempts to integrate BIM and GIS for the geometric representation and general visualisation of models. CityGML 2.0 has defined five LoDs to geometrically differentiate the multi-scale representations of 3D city models (Biljecki et al., 2016), as illustrated in Figure 3a. Both GIS and BIM embody objects in three-dimension based on a certain level of extraction from real-world phenomena. However, the method and model description are essentially different, GIS 3D models are Boundary-Representation-based surface models, whereas BIM models use Swept Solid representations (Liu et al., 2014). Figure 3b illustrates the geometric representation of the same objects using IFC and CityGML as spatial solids and surfaces, respectively (Nagel et al., 2009).



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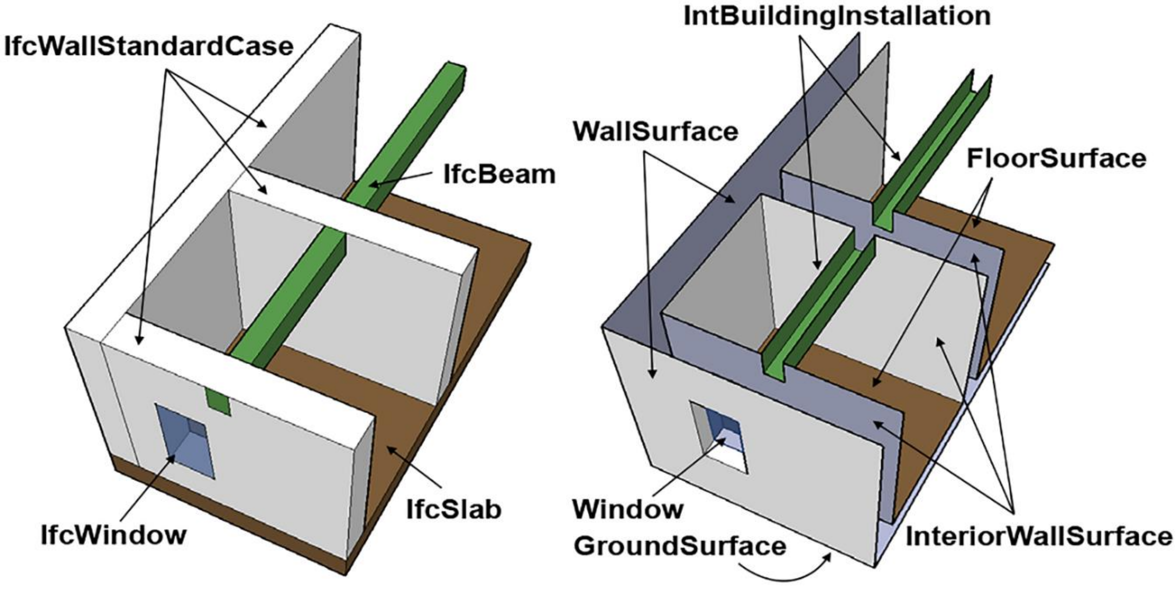


(b)

Figure 3 (a) The five LoDs defined by CityGML (Kolbe et al., 2005) distinguishing the graphic and non-graphic features of 3D city models from the coarsest representation of a two and half-dimensional Digital Terrain Model (DTM) to a high-resolution architectural model with detailed exterior and interior structures (Gröger et al., 2006). Reproduced from (Gröger et al., 2012), and (b) geometric representation of building storey in IFC (left) and CityGML (right). Reproduced from (Nagel et al., 2009).

Researchers have looked into methods that integrate BIM and GIS using frameworks consisted of numerous levels or groups. An example was presented by (Kang and Hong, 2015), where integration strategies were classified into five groups: schema-based, service-based, ontology-based, process-based, and system-based. Alternatively, a three-level grouping, namely the data level, process level and application level were proposed by (Liu et al., 2017c) and (Amirebrahimi et al., 2015). Data-level integration focuses on manipulating data models and structures to meet the requirements of applications. Creation of common models/standards or introducing mapping rules between data schema are generally involved in this process. Examples of the former include Unified Building Model (UBM) (El-Mekawy et al., 2012) and Land and Infrastructure Conceptual Model Standard (LandInfra) (OGC, 2016). Whereas mapping-rules-based unidirectional or bidirectional information transfer, with IFC and CityGML being the predominant standards for BIM and GIS, respectively can be found in (Berlo and Laat, 2010; El-Mekawy et al., 2011; Liu et al., 2014). The process-level integration employs both systems into a workflow to exploit their individual capabilities simultaneously without changing the data structures. By leveraging Semantic Web and Linked Data technology, this flexible and semantics-reserved method has been applied in shield tunnelling (Vilgertshofer et al., 2017) and utility tunnel maintenance (Lee et al., 2018; Wang et al., 2019b). The application-level engages modifying or rebuilding either a BIM or GIS tool to include the functions of the other, or using customised tools (i.e. plug-ins). This method is generally costly and inflexible since it involves reconfiguration or building of tools from scratch.

2.1.4 Global implementation

From a global standpoint, the adoption of digital construction has been recommended to promote advanced information exchange and management in the AEC industry. For example, the UK Government Construction Strategy (ERG UK, 2011) proposed a series of objectives, including the development of standards to enable collaborative working through BIM among members of the supply chain with the requirement of fully collaborative 3D BIM 'Level 2' as a minimum by 2016. Singapore vigorously uptakes BIM by mandating BIM use for major AEC projects in phases since 2013 and has rolled out its second BIM Guide outlining the deliverables, processes, and personnel/professionals involved when BIM is used in a construction project (BCA Singapore, 2013). In Germany, the Federal Ministry of Transport and Digital Infrastructure (BMVI) announced a Road Map for the implementation of BIM and IT-based technologies to the design and construction of major infrastructure projects (BMVI Germany, 2015). Most recently, BMVI and Federal Ministry of the Interior, Building, and Community launched a joint National BIM Centre of Excellence to speed up the digital revolution in construction (BMVI Germany, 2019). In Australia, both New South Wales (NSW) and Victoria have staged digital transition plans driven by their infrastructure upgrade schemes with NSW develops state-scale digital twin integrating digital engineering assets, BIM, and live feeds (NSW Australia, 2020a). Victorian Government has co-published the Victorian Digital Asset Strategy with the Office of Projects Victoria (OPV) to provide guidance for the implementation of digital engineering technologies in infrastructure projects to improve the interoperability and consistency of information management throughout the projects' life cycle (OPV Australia, 2019). Besides national legislations and governmental regulations, several project-based initiatives have been launched around the world to uphold the development of BIM for infrastructure. For instance, the French national collaborative research project – MINnD (IREX France, 2019) has marshalled more than 70 partners engaged in areas related to design, construction and maintenance of infrastructures to explore opportunities for enhanced information exchange and communication by implementing BIM.

2.2 Machine learning and computer vision

Big data and its closely related technologies such as cloud computing, Internet of Things (IoT) and artificial intelligence (AI) have achieved enormous attention in the past decade. AI branches that mimic human intelligence include machine learning, computer vision, and robotics, as shown in Figure 4. The advancements in both hardware and software for data will together benefit a wide range of fields, including design, construction, and maintenance of underground infrastructure.

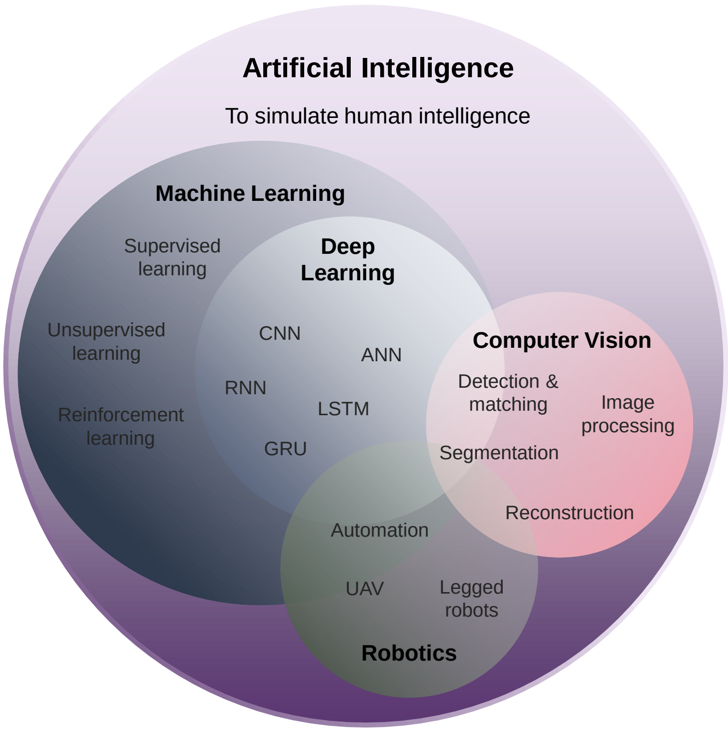


Figure 4 AI types to simulate human intelligence include machine learning, deep learning, computer vision, and robotics and frequently used terminologies in this paper

2.2.1 Machine learning

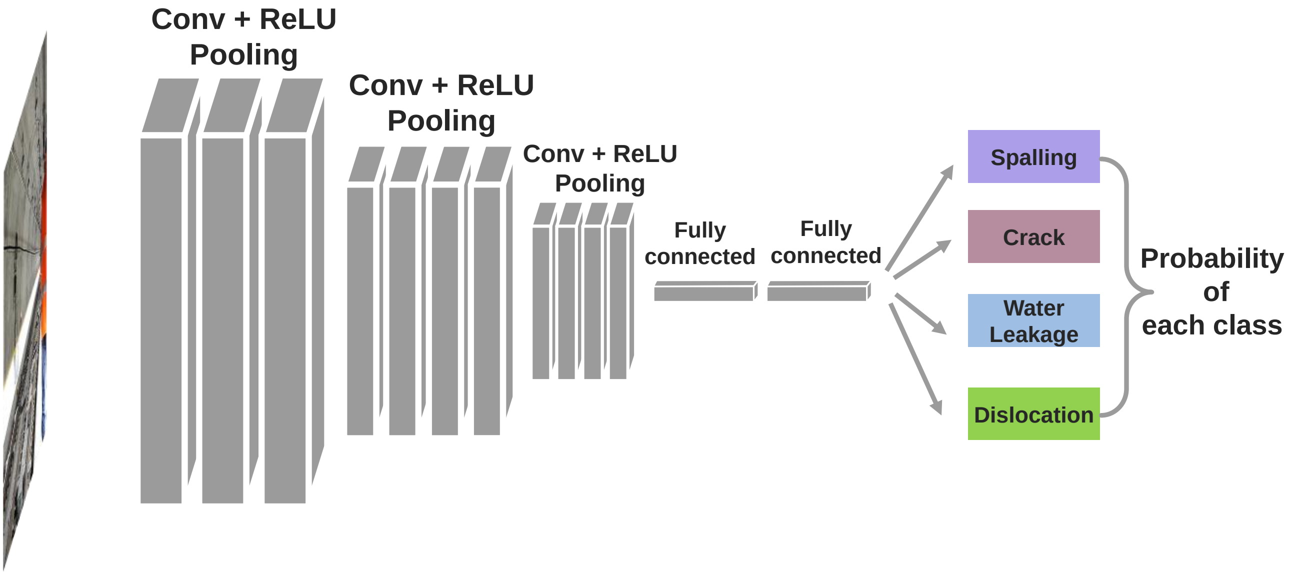
With a profound history that can be traced back to 1952 when Arthur Samuel developed the first game-playing program, machine learning was defined by the pioneer in 1959 as a "field of study that gives computers the ability to learn without being explicitly programmed" (Samuel, 1959). Machine learning algorithms are constructed to learn from data by automatically extracting patterns, with learning in this context defined by Mitchell (1997) as "a computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E." A manifold of tasks can be achieved with experience learned and performance evaluated by some measures. For example, in detecting cracks on tunnel segment, the task is to assign a label of "crack" or "no crack" to any given image taken inside a tunnel. The performance indicator to be enhanced could be the accuracy of this crack detector on classification, and the training experience might be a collection of images, each individually labelled to contain crack or not.

There are generally three types of machine learning: (1) supervised learning, (2) unsupervised learning, and (3) reinforcement learning. The crack detection task above is an example of supervised learning. The methods used in the discussed literature of this paper are mainly based on this type of learning, such as polynomial regression, artificial neural networks (ANN), and support vector machine (SVM). Machine learning techniques have been found useful in a diverse range of applications, including computer vision tasks, robotics, and autonomous vehicle control, speech and natural language processing, neuroscience research (Jordan and Mitchell, 2015). For the technical fundamentals of machine learning, readers are referred to textbooks (Jordan and Mitchell, 2015; Mitchell, 1997; Murphy, 2012).

2.2.2 Deep learning

Deep learning is a subfield of machine learning that has contributed to a majority of the recent success of the field. The architecture of deep learning algorithms is generally underpinned by ANN. Beyond the neuroscientific inspiration, the success of deep learning is mainly rooted in that deep learning networks adopt a more general learning principle characterised by multiple levels of composition, which has the key advantage of automatic feature extraction (LeCun et al., 2015). The procedure decomposes a complicated mapping target into a sequence of nested simple mappings, and each simple mapping is described by a layer in a deep learning model (Goodfellow et al., 2016). The incredibly large volume of data resulted from increased variety of optical-based systems, along with the growth in computational power, stimulates the development of deep learning. Among the deep network architectures, models based on convolutional neural networks (CNN) and recurrent neural networks (RNN) have been particularly successful in tasks associated with pattern recognition and image interpretation (Schmidhuber, 2015) and thus significantly accelerated recent advances in the field of computer vision (Spencer et al., 2019). For instance, CNN-based models such as the fully connected network (FCN) (Long et al., 2015), U-Net (Ronneberger et al., 2015) and Mask-R-CNN (He et al., 2017) have been used for object detection and image segmentation, and architectures based on RNN such as long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997) for image captioning (Alom et al., 2019). Figure 5a schematically illustrates CNN-based instance segmentation of tunnel images. Other examples can be found in (Guo et al., 2016). With the successful application of deep learning algorithms in computer vision tasks using 2D images, growing attention is paid to deep learning techniques in 3D data analysis since 2015, driven by the increasing access to 3D data in recent years. Multi-view deep learning proposed by (Su et al., 2015) and the voxel-based 3D CNN proposed by (Maturana and Scherer, 2015) are among the pioneering studies. Examples of 3D deep learning in change detection of civil infrastructure can be found in (Gomes, 2018; Zhang et al., 2017).

Ahmed et al. (2018) groups the 3D data representations into Euclidean-structured data and non-Euclidean data; the former includes descriptors, projections, RGB-D, volumetric (voxels and octree) and multi-view, and the latter contains point clouds, meshes and graphs. Euclidean-structured data can be learned with 2D deep learning algorithms, such as CNN, since it has an underlying grid structure, which allows global parametrisation and formation of a common coordinate system (Ahmed et al., 2018). For example, the 3D ShapeNets that illustrates a geometric 3D shape as a probability distribution on a 3D voxel grid and uses a Convolutional Deep Belief Network (Wu et al., 2015) to perform feature extraction. Another example is the Multi-view CNN as shown in Figure 5b that trains a standard CNN to recognise 3D shapes from a collection of their rendered views on 2D images (Su et al., 2015). Whereas non-Euclidean data that has an unordered structure is more challenging to be directly applied with established deep learning techniques. Qi et al. (2017a) pioneered a deep neural network named PointSet for 3D classification and segmentation on point clouds considering the unordered characteristics of the point sets. The PointSet ++ proposed by Qi et al. (2017b) improves on PointNet by considering local structures with increasing contextual scales.



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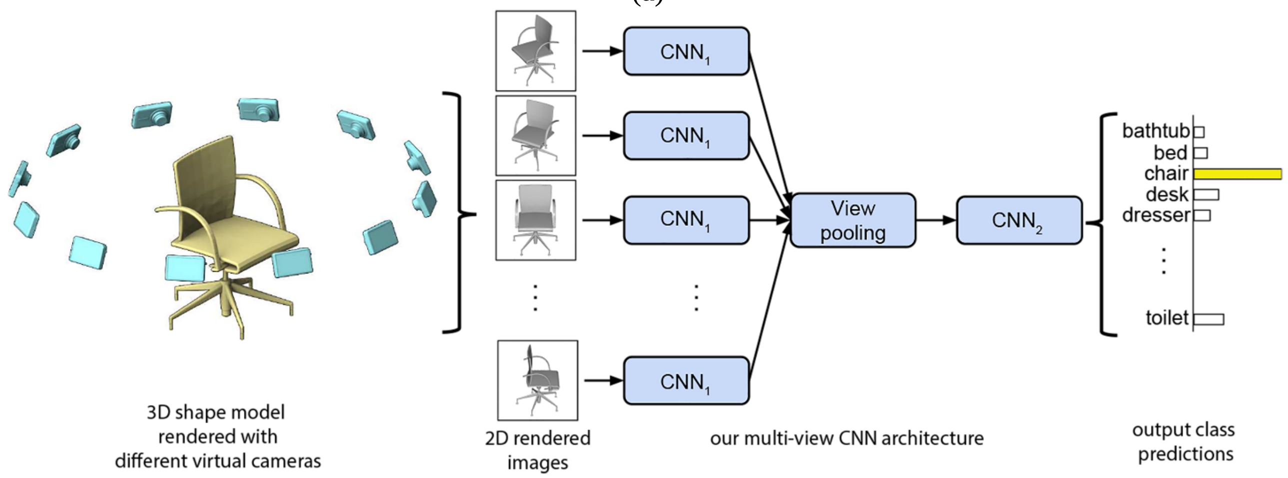


(b)

Figure 5 (a) Schematic of a typical CNN for instance segmentation of a tunnel, and (b) Multi-view CNN for 3D shape recognition. Reproduced from (Su et al., 2015)

Training and evaluating a deep neural network on abundant samples are especially crucial to improving the robustness of networks (Garcia-Garcia et al., 2017). The ImageNet (Deng et al., 2009) is one of the renowned image datasets conceptualised in 2006 that intended to provide easily accessible images for image- and vision-related research fields. Several renowned deep learning architectures, such as the AlexNet (Krizhevsky et al., 2012), VGG16 (Simonyan and Zisserman, 2014), GoogLeNet (Szegedy et al., 2015), and ResNet-50 (He et al., 2016) have competed in the annual ImageNet Large Scale Visual Recognition Challenge (ILSVRC) leveraging the database (Russakovsky et al., 2015). Other open-source datasets include the PASCAL VOC (Everingham et al., 2010), Microsoft COCO (Lin et al., 2014) and CIFAR-10/100 (Krizhevsky and Hinton, 2009). Ibrahim et al. (2020) provided a review of the application and opportunities of computer vision in tackling city complexities from the perspective of city layers related to the built environment, human interaction, transportation and traffic, natural environment, and infrastructure. Among the subdivided urban systems, there are a few city-level datasets, such as CamVid (Brostow et al., 2008), Cityscapes (Cordts et al., 2016), DOTA (Xia et al., 2018), and UAVid (Lyu et al., 2020) and several infrastructure-level datasets (Gao and Mosalam, 2020; Maeda et al., 2018; Maguire et al., 2018; Ren et al., 2020; Song and Yan, 2013; Zhang et al., 2016a). An example of the infrastructure-level datasets is the PEER Hub ImageNet Φ-NET, which contains more than 36,000 images for structural damage recognition based on service conditions, inspection tasks and laboratory simulation of extreme events (Gao and Mosalam, 2020). These methods normally employ two stages: (1) training a CNN object detection model to implement a crack patch classification, and (2) detecting crack patches on raw images to provide crack information for each detected patch. However, these datasets are collected mainly by 2D sensing devices and seldomly used in a real-time system.

2.2.3 Computer vision

Although deep learning outperforms other techniques in certain areas such as object detection and recognition, there are domains where traditional computer vision techniques still excel at, such as panoramic vision and 3D reconstruction (O'Mahony et al., 2019). Such examples can be found in (Fathi et al., 2015). Computer vision is an interdisciplinary scientific field that can be defined as the process of analysing images or videos so that useful information can be extracted in order to understand or represent the underlying physical world. Computer vision algorithms have wide applications, stereo matching, person tracking, and face detection are some examples of them (Szeliski, 2010). For the implementation of computer vision techniques in infrastructure, refer to the textbook (Brilakis and Haas, 2019), and for in-depth reviews focusing on specific computer vision techniques for concrete and asphalt civil infrastructure, readers are referred to (Koch et al., 2015; Spencer et al., 2019). As project transitioning from design to construction, then to operation, the as-designed model is supposed to be converted to an as-built model, which corresponds to the actual BIM data of the constructed facility and eventually to an as-damaged model that represents any variations of infrastructure condition (Koch et al., 2014). In these transitions, computer vision-based sensing systems provide essential means to capture and record the continuously evolving state of infrastructure and subsequently support decision-makings with this information supplied to BIM (Soga and Schooling, 2016). When semi-autonomous or autonomous platforms used for data acquisition are combined with machine learning, especially deep learning, information of the built environment can be managed to build knowledge and create values.

3. BIM for tunnelling and underground construction

Based on the selected publications of BIM for underground construction, a bibliometric network was established using the software tool VOSviewer, as shown in Figure 6. The network contains 35 nodes and 139 links based on keyword occurrences and association strength to help visually identify relationships and intellectual structure of the topics covered. In VOSviewer, closely related keywords are positioned in nodes close to each other while weakly related keywords are positioned far away from each other (van Eck and Waltman, 2014). Meanwhile, the thicker the line connecting two nodes, the stronger the link is between the two (Van Eck and Waltman, 2013). From the network illustrated, BIM is strongly bonded with “industry foundation class (IFC)”, “visualisation”, “3d modelling”, “monitoring” and “tunnelling”. The node of “tunnelling” is then strongly connected with “mechanised tunnelling”, “digitisation” and “conventional tunnelling”. Keywords that carry weaker link with BIM include “utility tunnels” and “GIS”. These topics having forecastable connections with BIM will be expanded in this section. Except for utility tunnels (e.g., electricity, steam, water supply pipes, and sewer pipes), which are essential city assets that could have greatly benefited from effective data management through sharing information and improving visualisation. However, given their different excavations and maintenances from railway/road/hydraulic tunnels, they will not be the primary focus in this paper. Some recent research progress in the planning, design and maintenance stages of utility networks with the assistance of BIM is discussed in these references (Ge and Xu, 2019; Haurum and Moeslund, 2020; Hu and Zhang, 2019; Lee et al., 2018; Li et al., 2019; Wu et al., 2019a; Yao et al., 2019; Yin et al., 2020; Yu et al., 2019a; Yu et al., 2019b). Refer to Zeiss (2020) for a summary of engineering cases and comments on the latest progress made by industry and government in underground utility.

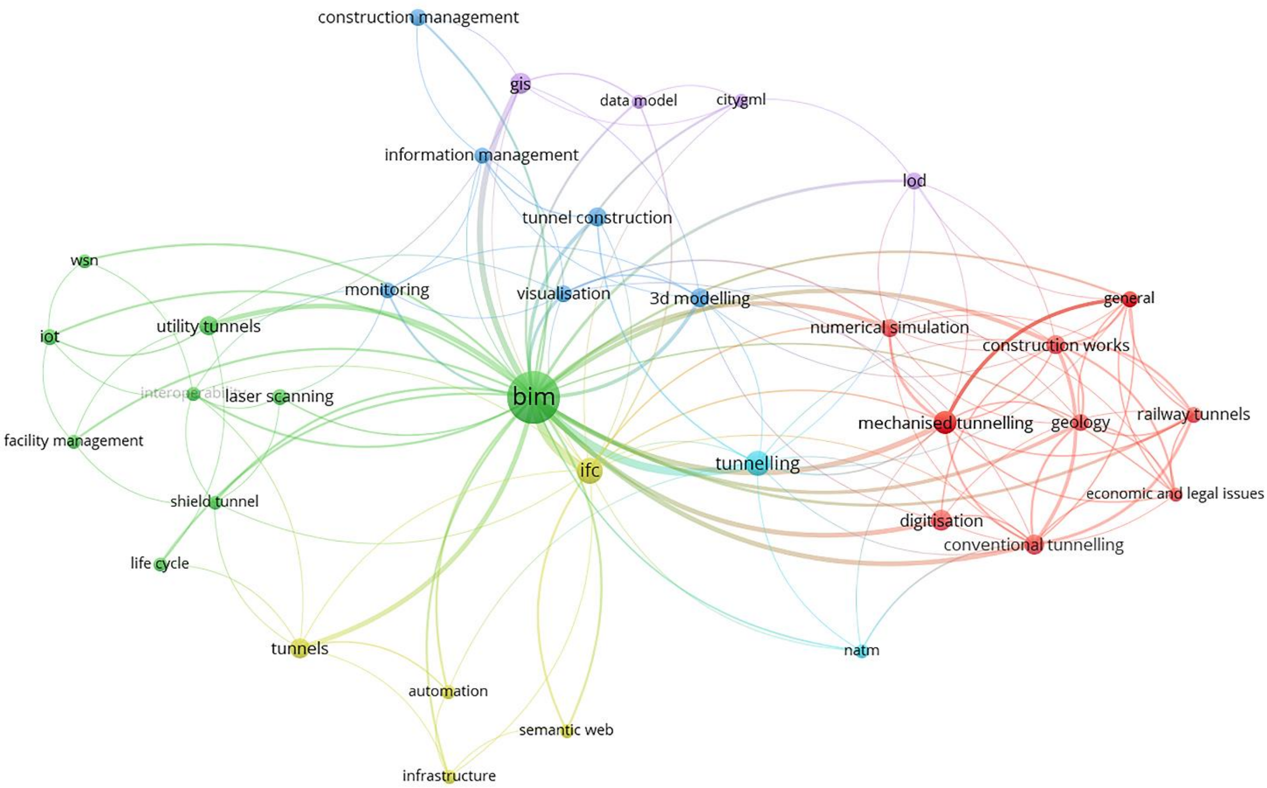


Figure 6 Mapping of co-occurrence of keywords (based on 212 selected papers; minimum number of occurrences was set to 3; keywords of total link strength less than 3 have been removed; unification of spellings was made that translate American English to British English; similar terms were merged, such as “engineering geology” and “geology”; terminologies abbreviated: bim – building information modelling; gis – geographic information system; ifc – industry foundation class; iot – internet of things; lod – levels of detail; natm – New Austrian Tunnelling Method; wsn – wireless sensor network).

The ground characterisation and geospatial location information are vital to the establishment of as-designed underground BIM model; therefore, this section will start by examining the relevance and development of 3D geological model (Section 3.1) and BIM-GIS integration (Section 3.2). Then the section continues to explore the advancement of BIM’s adoption within underground infrastructure, from the perspectives of data schema extensions (Section 3.3), geometrical and numerical modelling (Section 3.4), multi-component interactive platform (Section 3.5), and some typical innovative underground technologies in combination with the potential use of BIM (Section 3.6).

3.1 3D geological model for BIM

One of the major differences between surface and underground excavation is that the latter needs to deal with a complex geological environment. A sound understanding of the geological, geotechnical and geohydrologic conditions is necessary for the planning of underground infrastructure, and thus closely related to adopting BIM in underground construction.

3.1.1 Geological data schema

Geological survey organisations (GSOs) that exist in provincial, stage and national level are playing an important role in the long-term maintenance of geological data in terms of documentation, standardisation, utilisation, and dissemination. Individual and joint efforts by GSOs in standardising 3D geological data model exchange, initiatives include the European Geological Data Infrastructure (EGDI) aimed to be developed by a collaboration of 45 national and regional GSOs from 33 European countries under the Geological Surveys Research Area (GeoERA), and INSPIRE that aims to create a European Union spatial data infrastructure. Moreover, efforts have been dedicated to developing data schema for accommodating a transnational understanding of geological features. For example, GeoSciML (OGC Geoscience Markup Language) is a data transfer standard developed under a multi-national collaborative effort for the exchange of geoscientific information such as representations and description of features contained in a geological map (Russell et al., 2019). The GeologicFeature and MappedFeature concepts in OGC:GeoSciML proposed by Beaufils et al. (2020) is shown in Figure 7. A list of OGC implementation standards can be found from (OGC, 2020). Besides ongoing efforts in Europe, the Government Geotechnical Report Database (GGRD) Project undertaken by NSW Australia endeavours to improve data accessibility through collaboration with multiple governmental agencies (NSW Australia, 2020b). In addition, enhancing research efforts into 3D geological modelling is also an active direction, for example, the Loop project (Loop, 2019) coordinated through OneGeology (OneGeology, 2017) is based on multi-collaboration among Australia, Canada, France, Germany and the UK to provide open source implicit modelling solution.

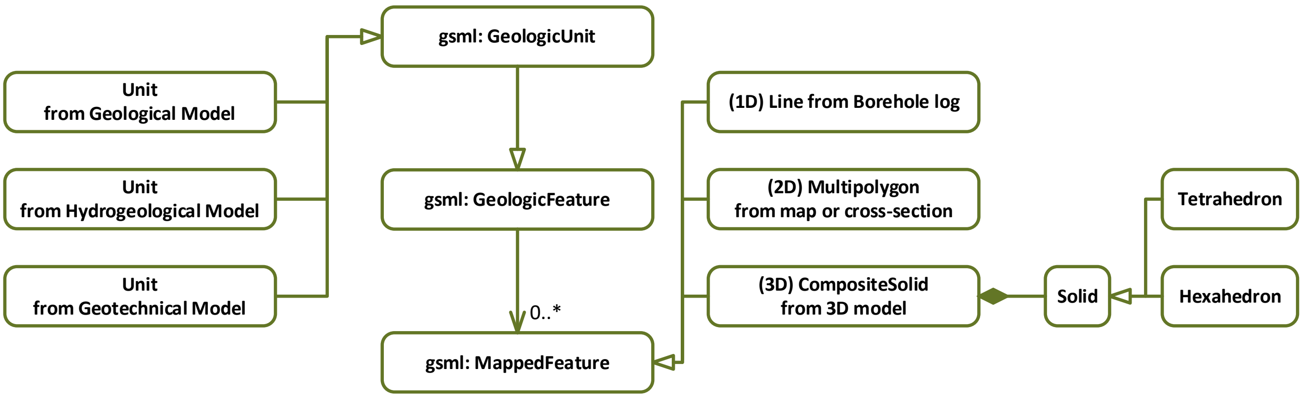


Figure 7 The GeologicFeature and MappedFeature concepts in OGC:GeoSciML. Redrawn after (Beaufils et al., 2020).

3.1.2 3D Geological modelling and quantification of geotechnical properties

Several studies have investigated the importance of understanding geological structures to underground construction (Aldiss, 2012; Klopcic et al., 2013; Rienzo et al., 2008). Depending on the geologic features of the ground, rock masses can be coarsely classified as an isotropic body with no apparent observant failure directions, or an anisotropic body possessing strong blocky features, indicating failure governed by weaker bedding planes. Subsequently, the potential failure mode around excavation, corresponding to the specific geological environment can be inferred. Moreover, the stability of excavation and effectiveness of support systems for anisotropic rock volume can only be fully assessed when an adequate geological model is established to allow considerations of discontinuities-associated potential failures (Hoek and Marinos, 2010).

Information used to form the geological model can be obtained based on either the project-specific ground investigation or existing knowledge of geological environments and interpretations made by geographers and geologists (Parry et al., 2014). After the data is acquired, an explicit or implicit approach is then followed to create the geological model. The explicit modelling involves the interaction and implementation of geological concepts by experienced geologists. In contrast, implicit modelling refers to the utilisation of software programs embedded with mathematical functions based on geological concepts. The accuracy of geological models established regardless the approaches taken are highly reliant on the data availability and quality (Pan et al., 2018) as well as the geological interpretations (Calcagno et al., 2008).

The quantitative data such as the rock quality destination (RQD) for geologic settings predominated with rocks, and information obtained from, for instances, cone penetration test (CPT) and standard penetration test (SPT) suggestive of soft-ground conditions provide the preliminary knowledge regarding the project's geological environment. This data, however, requires organisation and interpretation to vitalise. Therefore, good practices such as shown in Figure 8 that visualises the geotechnical parameters in the 3D model in combination with the tunnel design should be adopted for enhancing the interpretability of data.

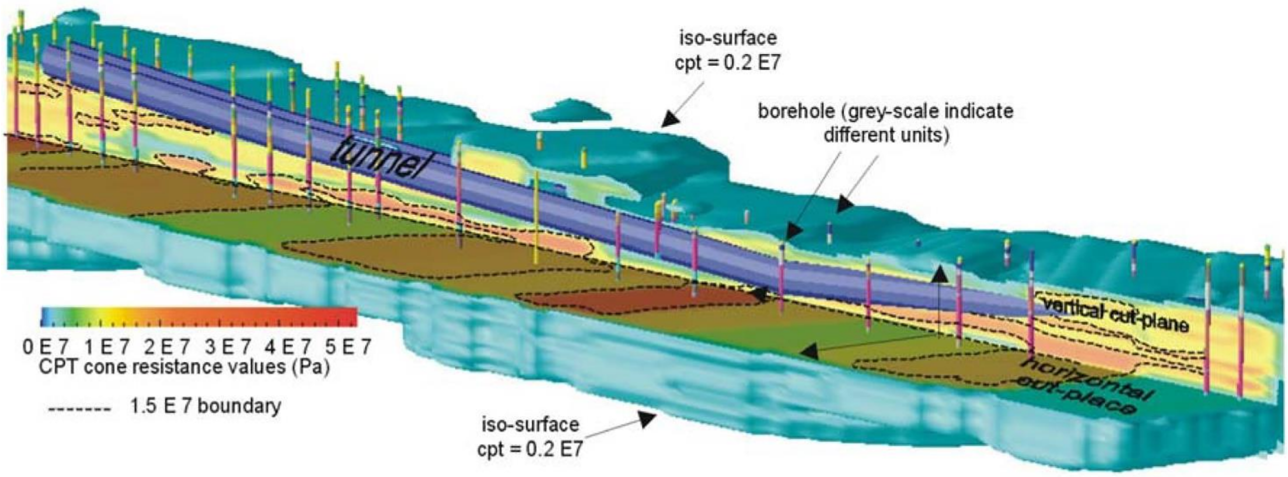
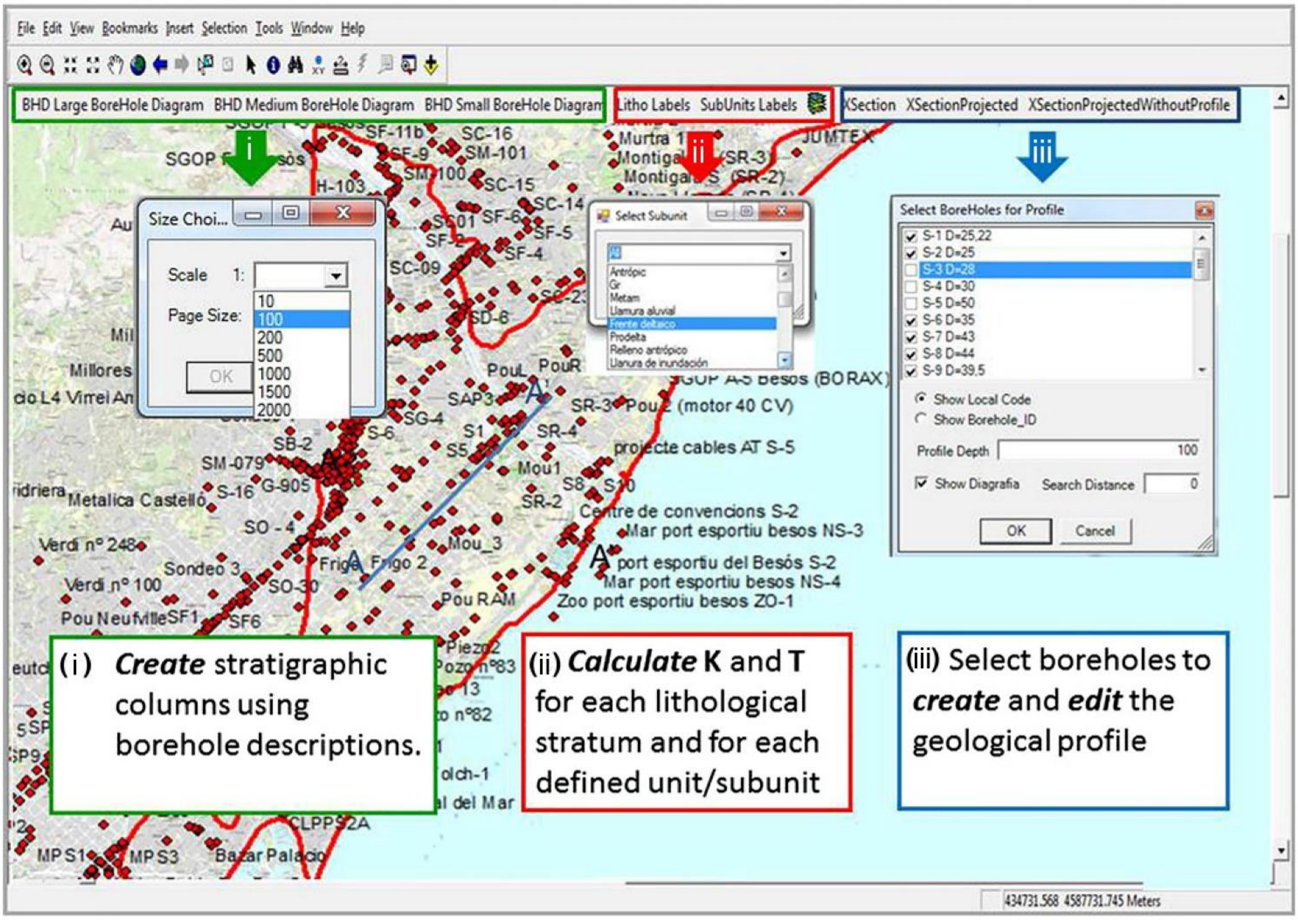


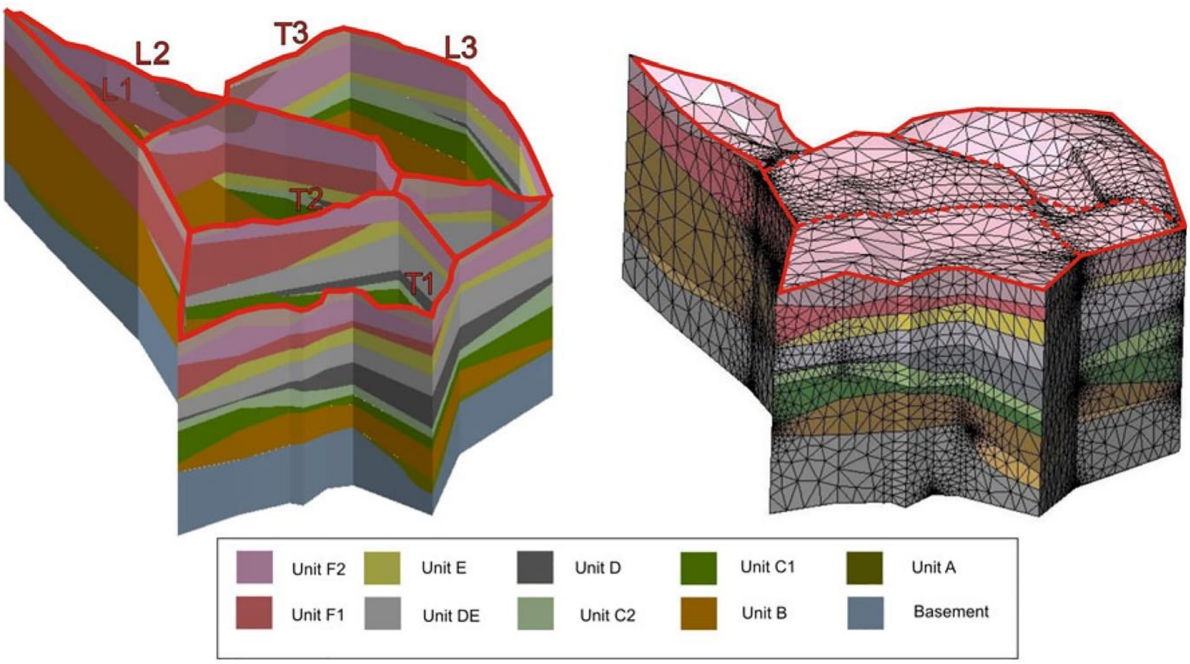
Figure 8 A 3D geological model constructed for a tunnel in soft ground (Heinenoord Tunnel, Netherlands) illustrated with CPT spectrum of boreholes. Reproduced from (Hack et al., 2006).

3.1.3 3D Geological model integrating GIS and BIM

As discussed above, a geological model serves as a bedrock for the design of the tunnel and underground construction; this is reflected in its capability to help improve design quality and identify, at the earliest stages, the critical geological issues by characterising the spatial distribution, stratigraphic settings and structural relationships of geo-objects. Digital management of both the historical and newly acquired data via computer-based systems such as GIS has gradually earned acceptance. Being the predominant tool to handle geo-referenced data, the development of GIS can be traced back to the last century (Coppock and Rhind, 1991) and through facilitating data maintenance, analysis and presentation (Huisman and By, 2009), the system and its analytical functions have been adopted widely to support geological information interpretation and model construction (Kaufmann and Martin, 2008; Kavoura et al., 2016; Song et al., 2018). Examples of establishing geological model using GIS applications can be found in (Velasco et al., 2013), which presents the stepwise procedures of establishing GIS-based 3D geological and hydrogeological models, with the GIS platform used to facilitate the stratigraphic analysis by administering required data with respects to the geographic location, as shown in Figure 9. Živec and Žibert (2016) describes the creation of 3D geological model for a tunnel project using GIS-based datasets and BIM inspired modelling techniques, and demonstrates the applications of the model, including geological structures extrapolation, rock mass characterization, and investigation planning. Moreover, Zhu et al. (2016a) proposed a GIS-based engineering geological system underpinned by the underground space information database for the evaluation of city urban underground space resources, as shown in Figure 10.



(a)



(b)

Figure 9 Steps and tools involved in a creation of stratigraphic columns, correlation and geological profile for a case study located in metropolitan area of Barcelona, NE Spain; (b) Geological model generated for the studied area and the corresponding meshed model. Modified from (Velasco et al., 2013).

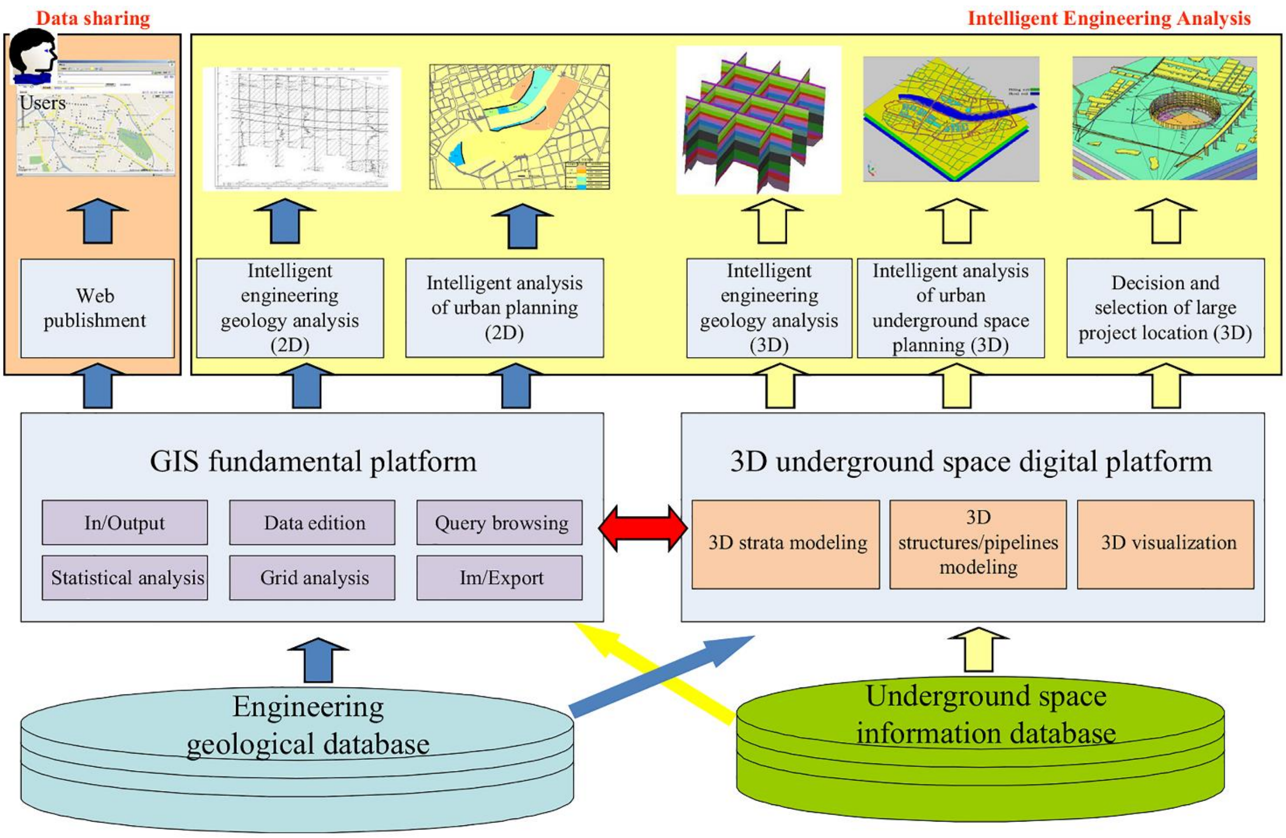


Figure 10 An intelligent GIS-based engineering geology system developed for resources evaluation of urban underground. Reproduced from (Zhu et al., 2016a).

From the standpoint of an institutional data paradigm where observations are maintained on a jurisdiction-wide basis, the corresponding regional geology data at Victoria state level, for example, is collected mainly for the purpose of mineral prospectivity with 3D geological models established at the regional scale. Urban or project-scale models of higher precision are often not publicly accessible and subjected to proprietary. To overcome the data sharing challenges, countries such as Germany and the Netherlands are making publicly available geological models and all relevant data, such as the "Borehole Map Germany" (BGR Germany, 2019) and "Data and Information on the Dutch Subsurface (DINOloket Netherlands, 2019)" (see Figure 11). Moreover, a sensible degree of data openness has been leveraged by countries like Singapore and the UK to develop large-scale geological understanding incorporating GIS databases. For example, the data of up to 60,000 boreholes drilled throughout Singapore was collected and compiled in a GIS system to facilitate the establishment of 3D geological model for the entire country (Pan et al., 2018), with a web-based geo-data modelling and management system, GeM2S developed for its future underground projects (Pan et al., 2020), as shown in Figure 12. Moreover, 2D geospatial datasets, including the hydrogeological GIS are used for the application of a 3D geological model maintained to support the sustainable development of urban underground at Earls Court, London, UK (Price et al., 2018).

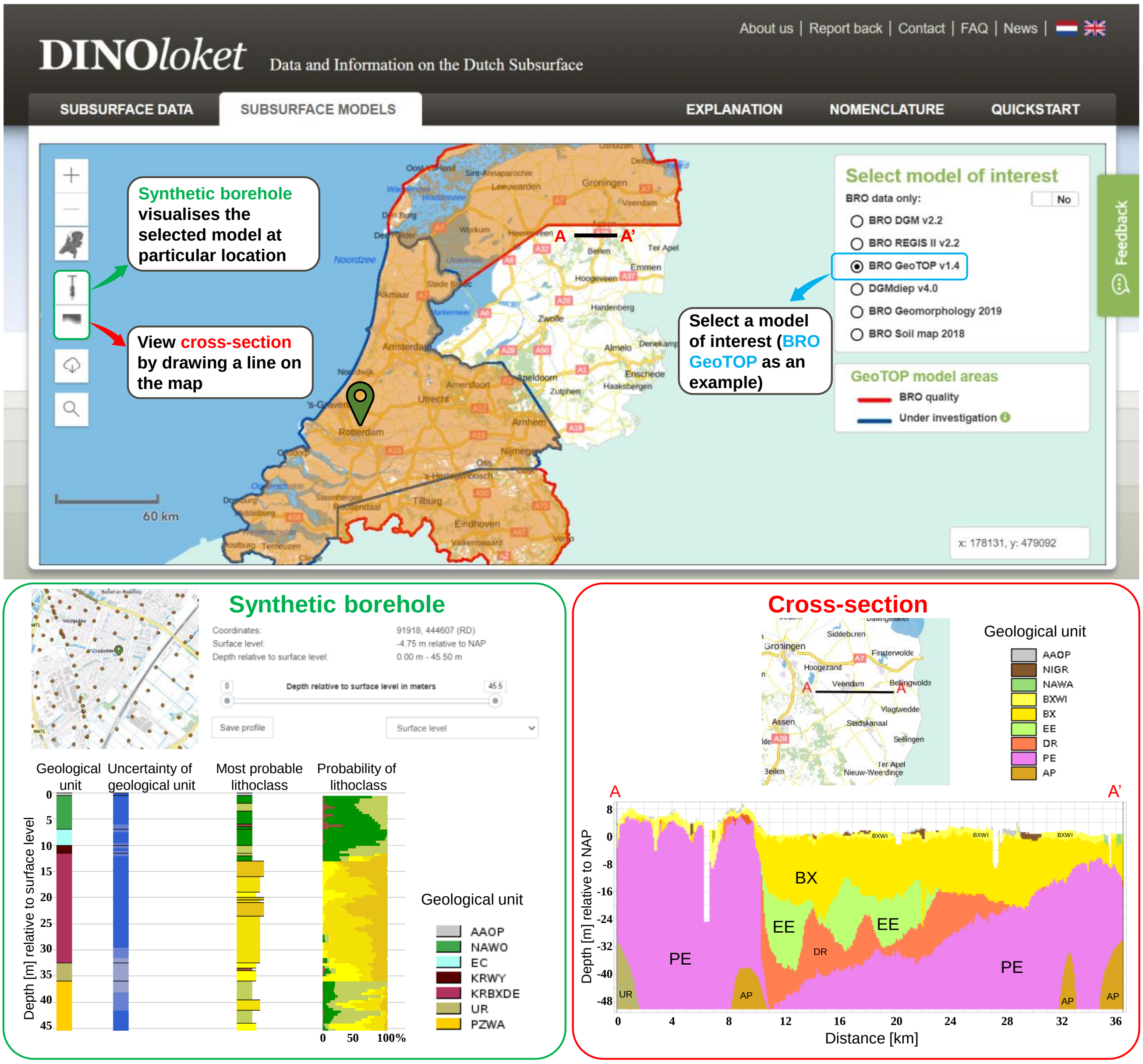


Figure 11 Demonstration of using DINOloket for creating synthetic borehole and cross-section; Both scenarios engaged model selection and user-defined location; the results are shown on the bottom. Accessed from: https://www.dinoloket.nl/en/subsurface-models

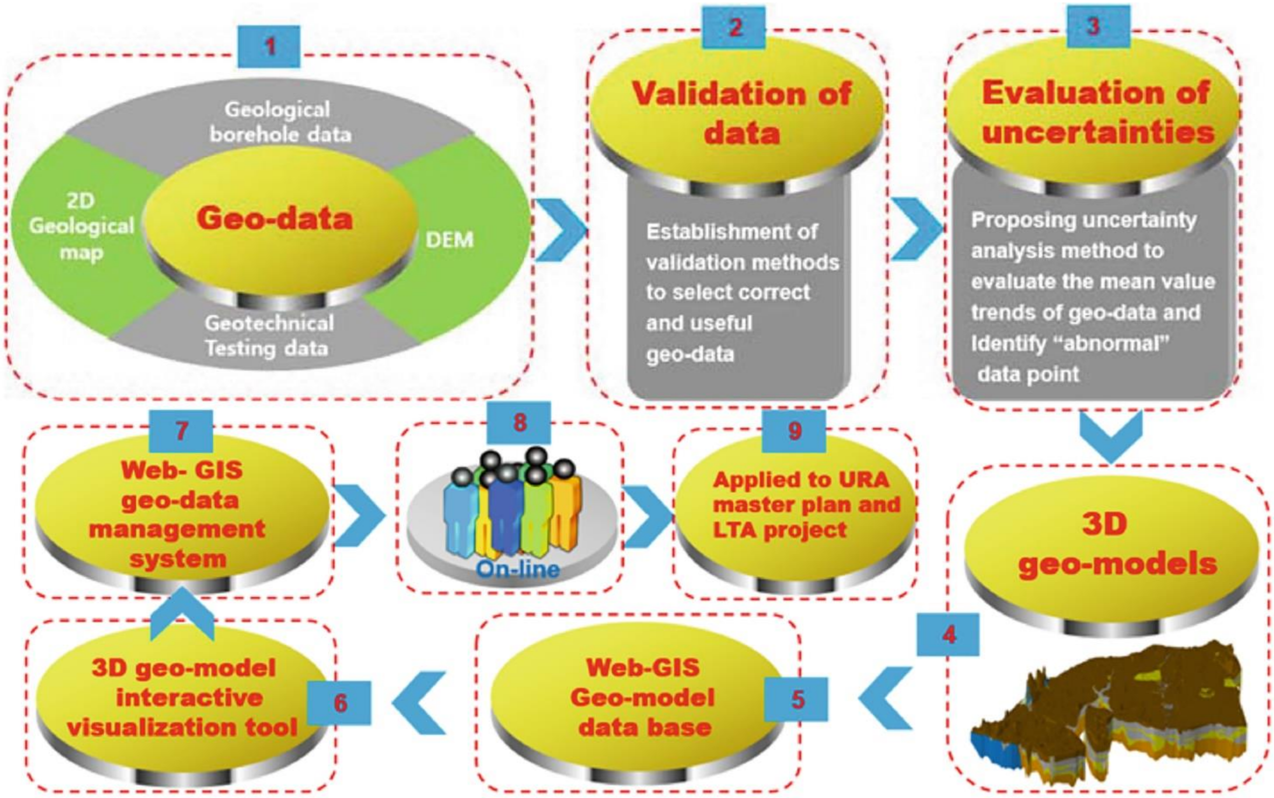


Figure 12 Workflow of a web-based 3D geo-data modelling and management system (GeM2S). It consisted of 9 steps that begin with collection, processing and evaluating the geo-data (steps 1-3), moving on to establishing a series of collaborative management tools incorporating web-GIS and 3D geo-model (Steps 4-7), and progressing to online applications implementing the tools to Singapore's urban redevelopment master plan (URA) and land transport projects (URA) (Steps 8-9). Reproduced from (Pan et al., 2020).

Efforts have also been devoted to establishing platforms for more automated and systematic geological quantification and interpretation using GIS. For example, Utsuki and Tsuruta (2018) describe a centralised management system incorporating artificial intelligence, construction information modelling, and image processing technology to help determine the geological conditions of the excavation sites. In addition, jurisdiction-wide model establishment combining building information and geological data, such as the joint research project between the Swiss Cadastral Survey and the University of Applied Sciences of Geneva has proved that there exist enormous potentials for better standardisation and multidisciplinary collaboration. Figure 13 illustrates the overall model incorporating surface and subsurface building information and geological data (Baumberger et al., 2019).

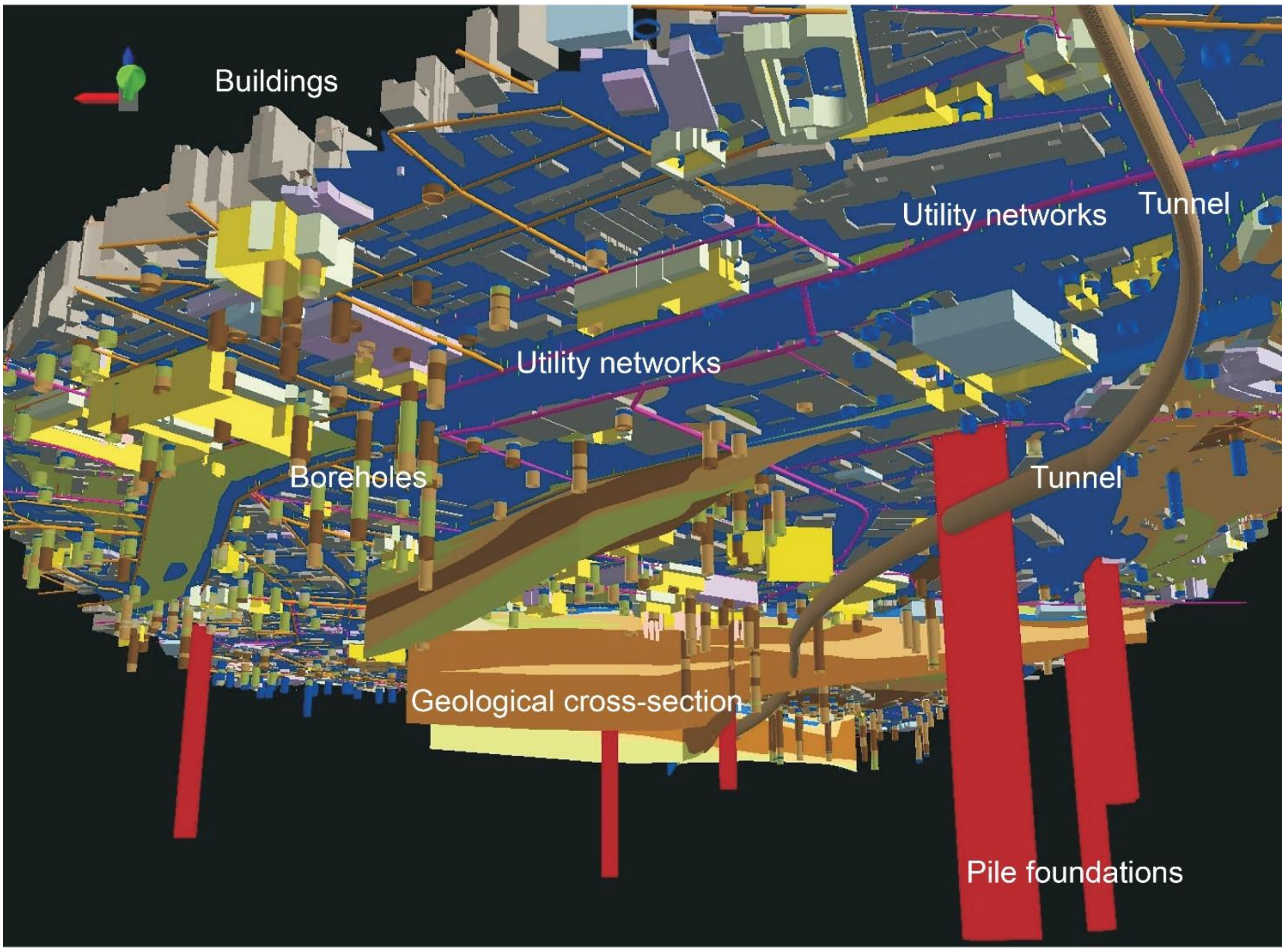


Figure 13 Integrated model of the city of Geneva incorporating surface and subsurface building information and geological data. Modified from (Baumberger et al., 2019).

3.2 GIS for BIM

GIS facilitates more than the spatial context for ground conditions, but also the localisation for physical constraints and emergency situations. Provision of GIS services has been found in earlier lifecycle stages of an underground infrastructure project's lifecycle. Included are route design and site selection of utility networks and rock cavern (Cheng and Chang, 2001), digital recording of geological and geomechanical surveying data during tunnel excavation (Thum and Paoli, 2015), as well as supporting risk assessment of geohazards such as water inrush during tunnel construction (Li and Li, 2014). Moreover, GIS-based monitoring of tunnel deformation (Liu et al., 2009), underground mine subsidence (Li and Li, 2014), mining-induced surface deformation (Spreckels et al., 2001), underground pipeline surveying (Zhang et al., 2016b) and underground utilities mapping integrating augmented reality (Fenais et al., 2019) have also been implemented. In addition, Borrmann et al. (2015) proposed an IFC-based multi-scale tunnel model inspired by the CityGML's intrinsic LoD representations.

A number of online GIS-based application platforms are maintained at different administrative levels. For example, AURIN, the Australian Urban Research Infrastructure Network, provides integrated GIS, data release and delivery service for researchers, industry and all levels of government. AURIN facilitates access to a large data collection from both public and private sources through the AURIN “infrastructure”, including a portal, an application programming interface, and a map. Application of AURIN portal in browsing the geological map (in polygon form) of the Central Business District (CBD) of Melbourne, Australia, as illustrated in Figure 14. Engaging QGIS – an open-source desktop GIS application, an example of coordinating GIS datasets GIS data for major infrastructures, such as the currently ongoing Metro Tunnel Project in Melbourne is shown in Figure 15.

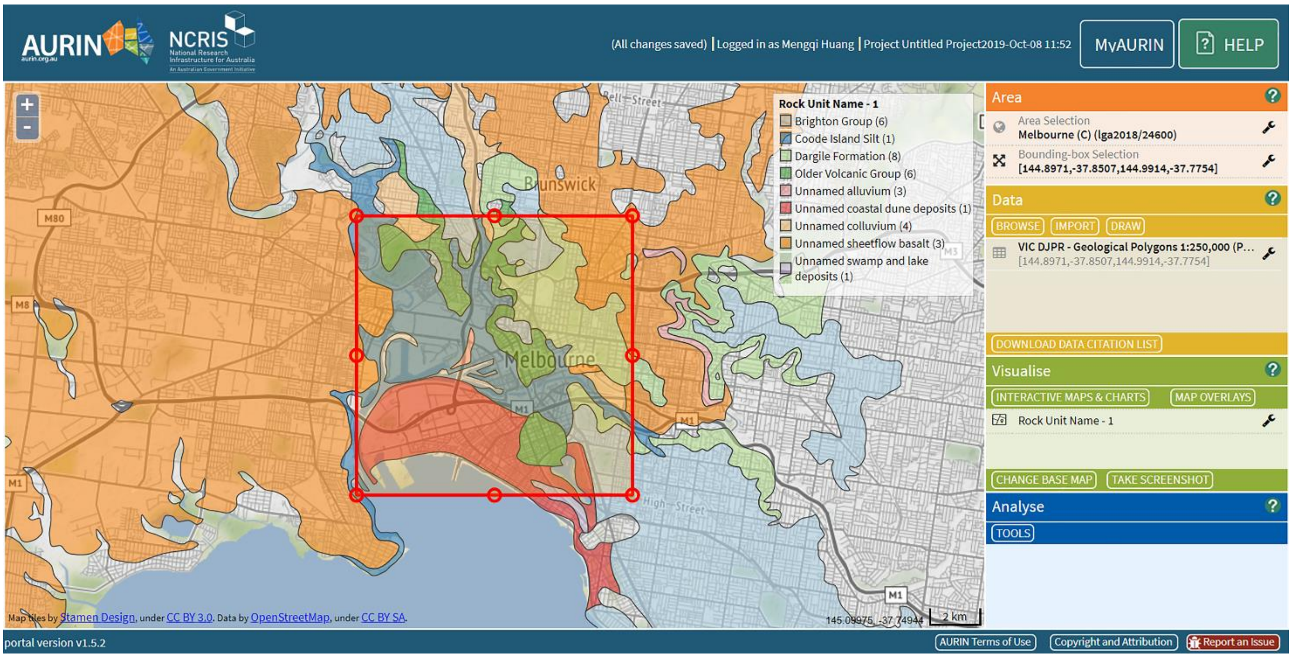


Figure 14 Demonstration of using AURIN Portal v 1.5 (Accessed from: https://portal.aurin.org.au/) to create a geological map leveraging GIS. The new project starts with Australia selected as the highest level of geography. Melbourne CBD (Local Government Areas in 2018 with code 24600) was then selected and placed with a bounding box (red rectangle, activating and dragging the red circles to reshape if required); For data retrieval, the keyword “geology” was used for accessing relevant dataset. The geological polygons at a scale of 1: 250,000 were selected and added for visualisation; using function of “Interactive Maps & Charts”, polygons were mapped with the attribute “UNITNAME” to produce the resulted map.

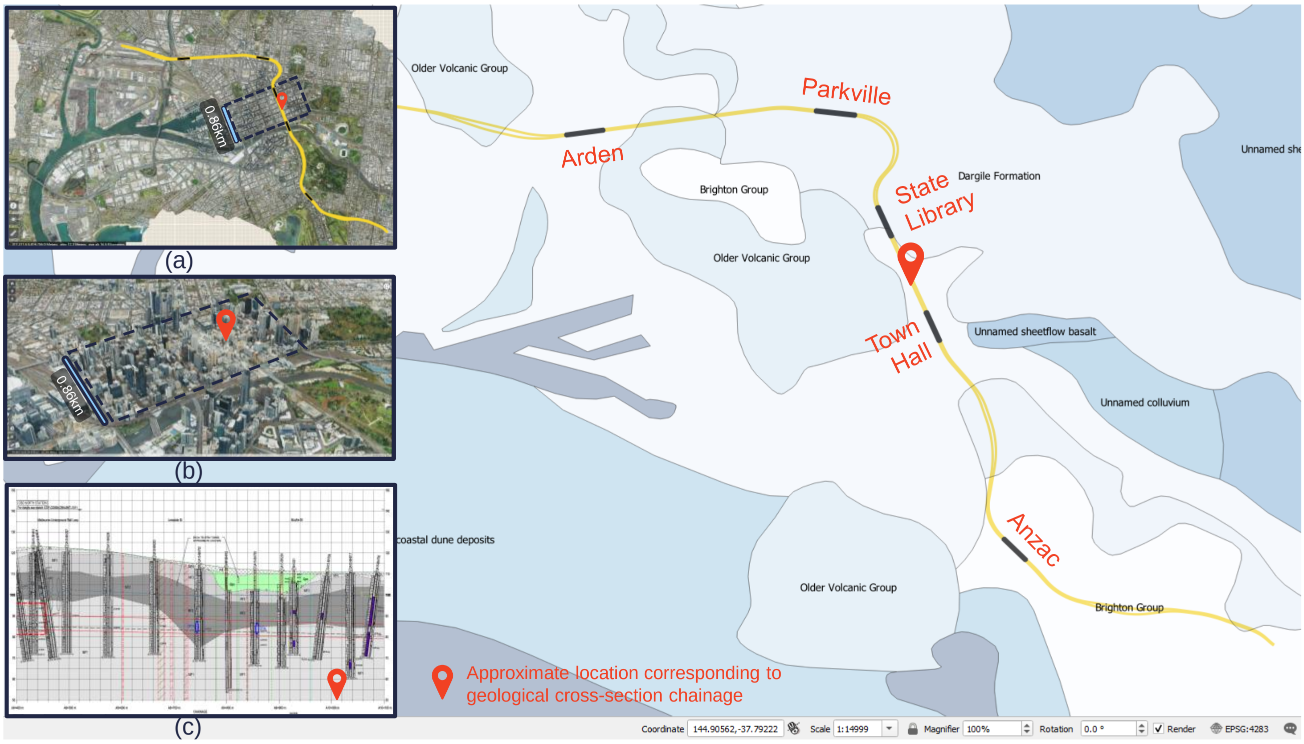


Figure 15 Coordinated visualisation of tunnel tracks and station entrances of the Metro Tunnel Project in Melbourne. The project GIS data can be accessed from https://unimelb.libguides.com/victorianmapresources/victorianGISdata. Both the geological map retrieved from AURIN and the project GIS data in shapefile can be imported to QGIS for visualisation and interpretation; (a) tracks and station entrances artificially positioned on a perspective view of a 3D textured mesh of city of Melbourne supported by GIS web-viewer (accessed from: https://cityofmelbourne.maps.arcgis.com/apps/webappviewer3d/index.html?id=b555219a327b4535a89d8ec6e97780cf; source data can be downloaded from https://data.melbourne.vic.gov.au/Property/City-of-Melbourne-3D-Textured-Mesh-Photomesh-2018/d5tb-r7a6), (b): enlarged view concentrates on the area of Melbourne CBD with densely distributed high-rise buildings, and (c) the geological cross-section corresponding to the location of a section of tracks.

Finally, there have also been scientific initiatives to investigate the state-of-the-art implementation of open standards towards integrating BIM and geospatial views. The GeoBIM benchmark project, for instance, aims to "provide a framework describing the present ability of existing software tools to use CityGML and IFC models and understand their performance while doing so", and one of the tasks carried out during the examination is the conversion between the two schemas (GeoBIM benchmark, 2019). Reports on the initial and intermediate results of the projects can be found in (Noardo et al., 2019; Noardoa et al., 2019).

3.3 IFC extensions for tunnelling

The tunnel construction methods can be broadly classified into mechanised and conventional tunnelling approaches by whether a tunnelling boring machine (TBM) is involved. There has been extensive research covering aspects concerning both mechanised and traditional tunnelling. Included were TBM performance in adverse ground conditions (Barla and Pelizza, 2000; Barton, 2000; Gong et al., 2016; Zhao et al., 2007), the influence of mechanical properties of geomaterials over tunnelling performance (Liu et al., 2017a; Nilsen et al., 2006; Ramezanzadeh et al., 2008), numerical simulation of excavation process (Kasper and Meschke, 2004;

Lambrughi et al., 2012; Mroueh and Shahrour, 2008), settlements induced by tunnel construction (Fargnoli et al., 2013; Koukoutas and Sofianos, 2015) as well as monitoring of operation (Huang et al., 2018c; Shen et al., 2014).

One fundamental premise of BIM is to create a collaborative environment by providing interoperability and consistent data structure. This section examines the existing customised extensions of IFC-schema for representing tunnelling-related content. However, standardisation of IFC-schema for tunnel and its related facilities (e.g. stations) is still in progress (bSI, 2019b). This implies that there could hitherto exist significant ambiguities in terms of format, process and meaning of the project product model. Without the universality, the concept of "Open BIM" that stresses the use of neutral data exchange formats (Borrmann et al., 2018) cannot be fully implemented.

3.3.1 Conventional tunnelling

Conventional tunnel methods such as the New Austrian Tunnelling Method (NATM) and the Analysis of the Controlled Deformation in Rocks and Soils (ADECO-RS) do not engage TBMs, so that excavation and support installation are performed as separate procedures, which is denoted as cyclic tunnel advance. Karakuş and Fowell (2004) and Lunardi (2008) detail the tunnelling philosophies of NATM and ADECO-RS.

The German Tunnelling Committee, DAUB (2019) introduced a new term "Level of Geometry (LoG)" along with the recommendations to future standardisation and activities within the scope of BIM in tunnelling. Defined as the "degree of geometrical detailing of the model with reference to the modelled content of the construction elements", Figure 16 illustrates the increasing geometrical complexity for conventional tunnelling on a scale from LoG 100 to LoG 400. In terms of IFC schema developed for conventional tunnelling, Lee et al. (2016) extended the existing IFC model by comparing it with the design elements for a NATM tunnel, and added the identified elements to fully represent the NATM tunnel. The schema expansion following the structure of IFC data model (i.e., in hierarchical order) included both the spatial and physical entities as well as their corresponding attributes and relationships.

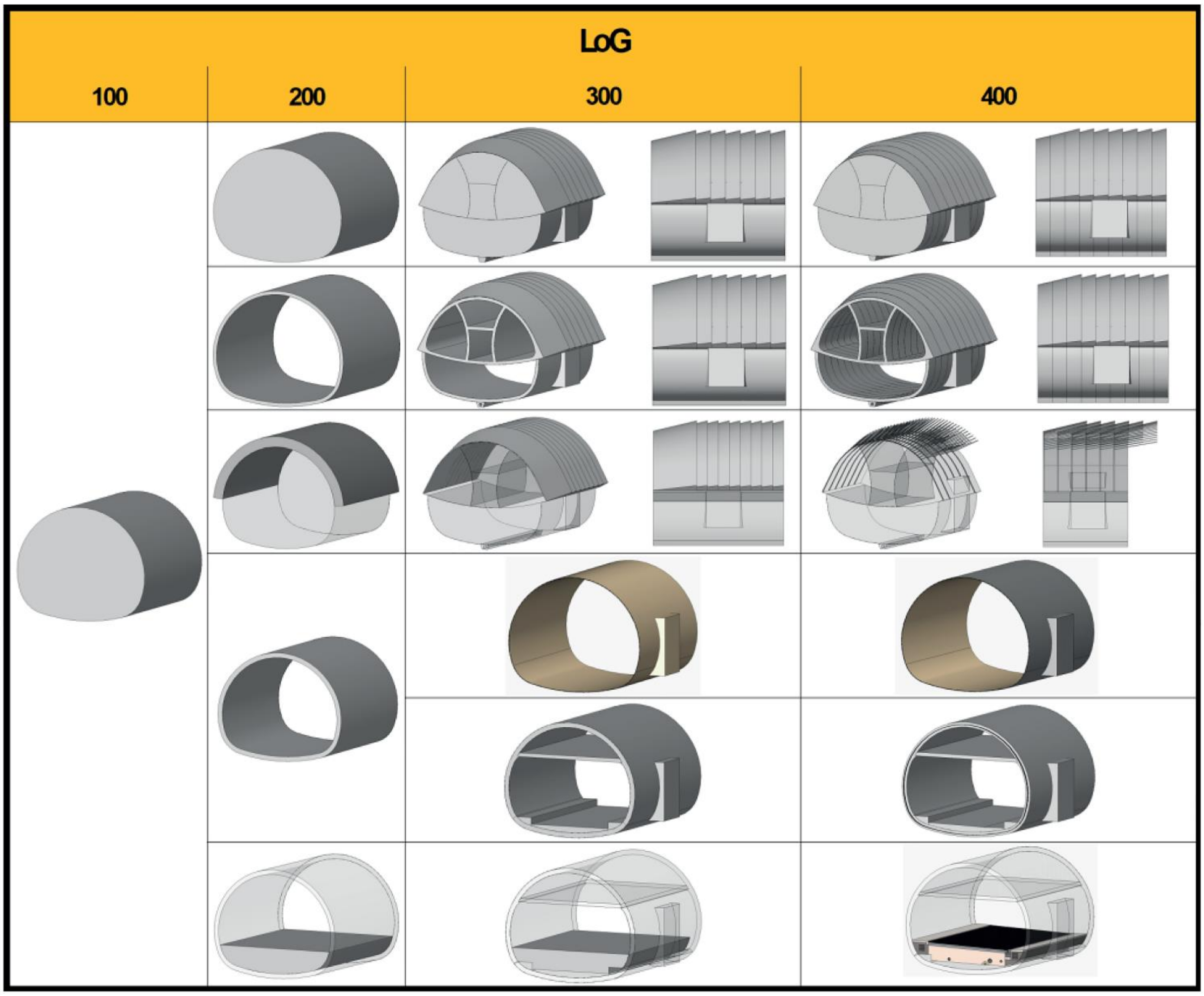
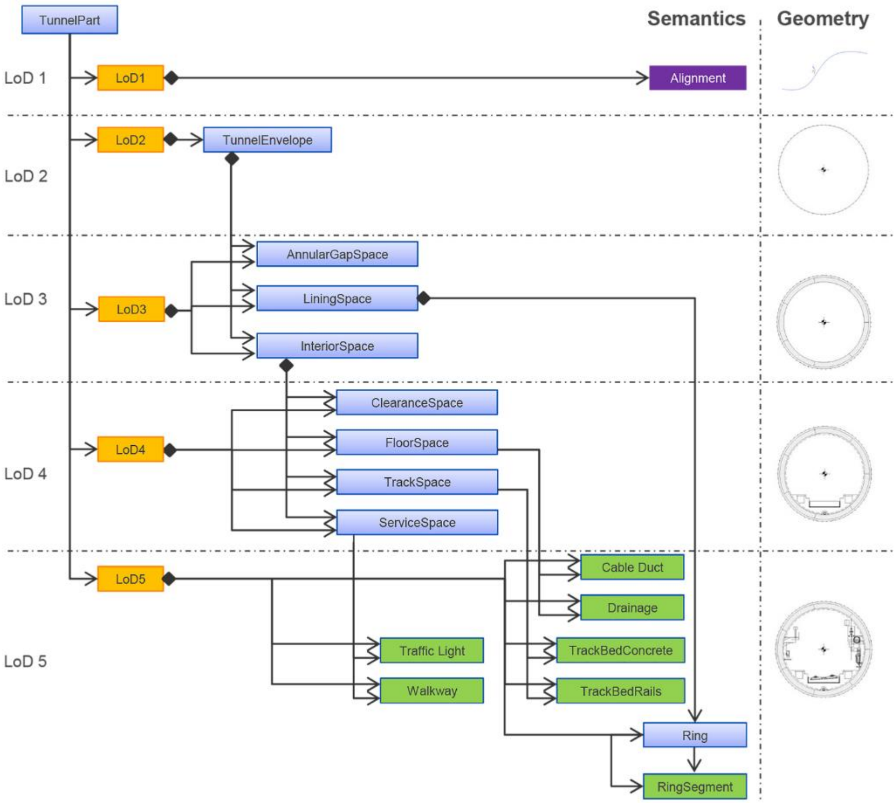


Figure 16 Level of Geometry (LoG) in conventional tunnelling. Reproduced from (DAUB, 2019).

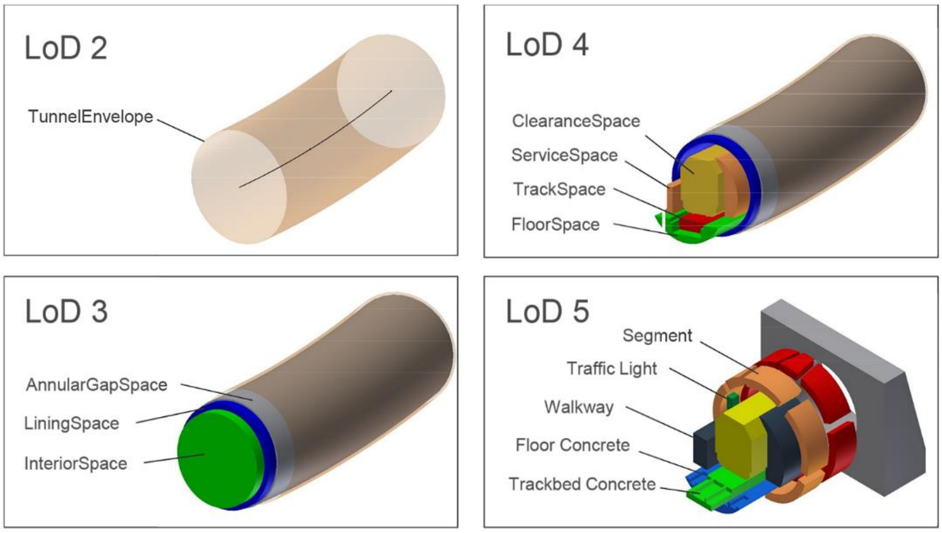
3.3.2 Mechanised tunnelling

Mechanised tunnelling implies the use of TBM that excavates the ground driven by a cylindrical cutting wheel. TBMs are generally classified into open TBMs and shield machines. In case of open TBM tunnel advance, if necessary, the excavated rock is supported with shotcrete, anchors and steel arches. On the contrary, shield TBM advance and installation of segmented tunnel lining is carried out under the protection of a steel shield that advances along the tunnel axis, resists surrounding ground pressure while preventing water inflow until the installation of temporary or final support lining is completed (Maidl et al., 2012). Since the excavation and support implementations are carried out almost simultaneously, shield tunnelling is referred as continuous tunnel advance.

In recent years, the research in the area of information modelling for underground infrastructure was driven in an effort to extend IFC data schema, covering contents related to the activities, machineries and systems of underground infrastructure. Through the initial efforts of (Yabuki, 2009), a generalised data model for shield tunnels, named IFC-ShieldTunnel was established to include tunnel-specific members, such as shafts, segments (of various types), waterproofing elements, segment joint elements, and ring joint elements. In the later research, Yabuki et al. (2013b) proposed a conversion technique through effective mapping, which enabled the automatic data adaption from Revit Structure 2011 (i.e. IFC 2×3) to IFC-ShieldTunnel. Borrmann and Jubierre (2013) have presented a comprehensive product model based on the previous work by Yabuki et al. (2013b) with a focus placed on preserving semantic-geometric coherence of the model. Figure 17 illustrates the proposed shield tunnel product model, which is a generalised data model that empowers the exchange of data specifics of a shield tunnel, including geometric shapes, properties, and relationships (Borrmann and Jubierre, 2013).



(a)



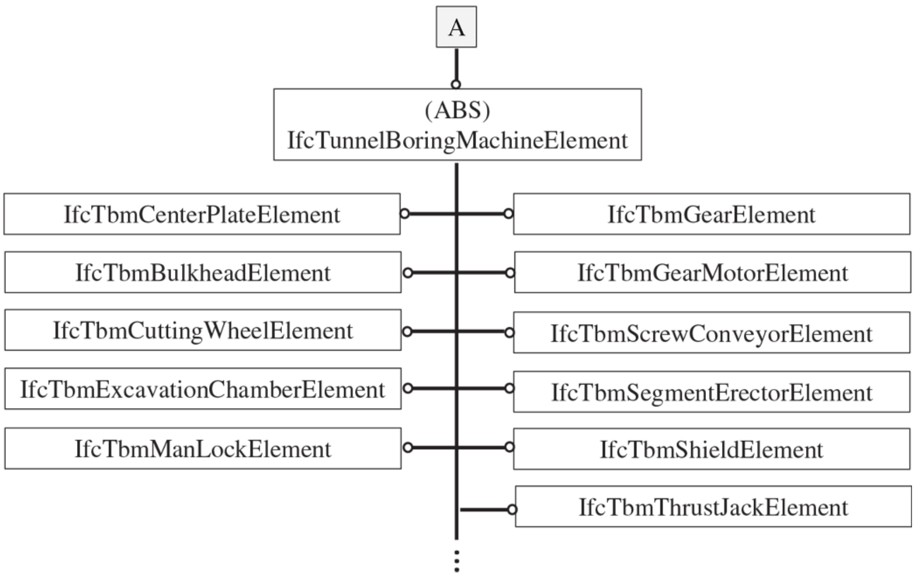
(b)

Figure 17 (a) A proposed shield tunnel product model incorporating (b) a coherent multi-scale representation of semantics and geometry. Reproduced from (Borrmann and Jubierre, 2013).

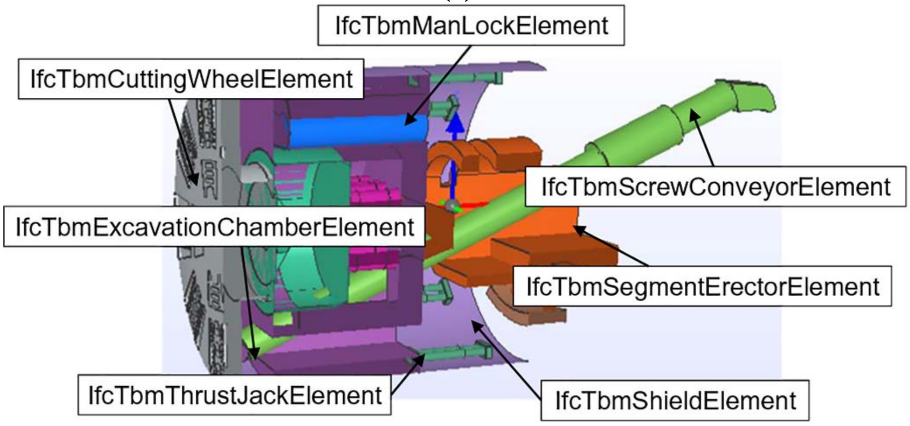
Vilgertshofer et al. (2016) further enhanced the approach by placing emphasis on the downward compatibility of the expanded IFC data schema, which considered the implementation of semantic entities associated with a particular LoD to prepare for LoD-dependent visualisation in any IFC-viewers. Zhong et al.

(2018) presented a similar approach to develop an IFC-based data model of shield tunnel. Based on the product model, a shield tunnel assembling method was proposed as well as a parametric modelling method. Additionally, Zhou et al. (2018) presented an extended IFC data model compatible with a typesetting algorithm designed for deviation control during the segment assembly of a shield tunnel, and a series of spatial and physical entities for the process of segment assembly have been identified and combined in the extended IFC schema. The extension model based on IFC has been applied in the Wuhan Yangtze River Tunnel in China to confirm the validity.

Research has also been directed to model the TBM by IFC-compatible classes. Hegemann et al. (2012) introduced a detailed IFC product model for a specific type of TBM commonly used in unstable ground conditions – Earth Pressure Balance (EPB) machines. A series of components consisting of the EPB machines were considered in the newly established IFC product model, such as the cutting wheel, excavation chamber, and screw conveyors. Similarly, Koch et al. (2017) presented a tunnel information modelling framework that accommodates four interactive subdomain models, including a ground model, a boring machine model, a tunnel lining model, and a built environment model. These models were individually established and integrated via an IFC environment (Figure 18). Gueulet and Milesy (2018) proposed a 4D visualization tool for TBM worksites that promoted the instant generation of 3D models owing to database connection. Models integrated into the system include the TBM model, segmental lining model, 2D tunnel alignment, geological block model, stations BIM models, and city buildings model.



(a)



(b)

Figure 18 (a) Added element classes within extended TBM IFC model, and (b) part of modelled TBM elements corresponding to (a). Reproduced from (Koch et al., 2017).

The concept of differentiating morphological features of building parts has been extended for tunnels and components involved in tunnelling projects. Borrmann et al. (2014) introduced a multi-scale modelling approach that considers the widely different scales in an inner-city tunnelling project. The methodology is composed of two aspects aiming at building a multi-scale model of shield tunnel and a conceived collaboration platform. The shield tunnels constructed in the project were modelled with five different LoDs representing the different levels of abstraction required in the planning stage. The collaborative design is achieved by employing procedural modelling techniques, which help establish explicit dependencies between the geometric entities on different LoDs and facilitate consistency preservation between LoDs. Osello et al. (2017) proposed a BIM-based methodology for implementing in a tunnel project. To determine the appropriate LoD for the respective project, it examined the notion of "level of (model) definition" in accordance with PAS 1192-2:2013 set out by the British Standards Institution (BSI). Level of definition includes both "level of model detail" and "level of information detail", i.e. degree of graphical and non-graphical details of the models. In this study, the level of definition 4 was ascertained to provide sufficient parametric information required in developing the BIM model of the tunnel. Moreover, Ninić et al. (2020) introduced a multi-level information and numerical modeller for mechanised tunnelling projects. The work emphasises on the flexibility of modelling components of building, tunnel lining and soil at different LoDs to predict tunnelling-induced damage to buildings, soil stability around excavation and damage in the segmental lining (Figure 19).

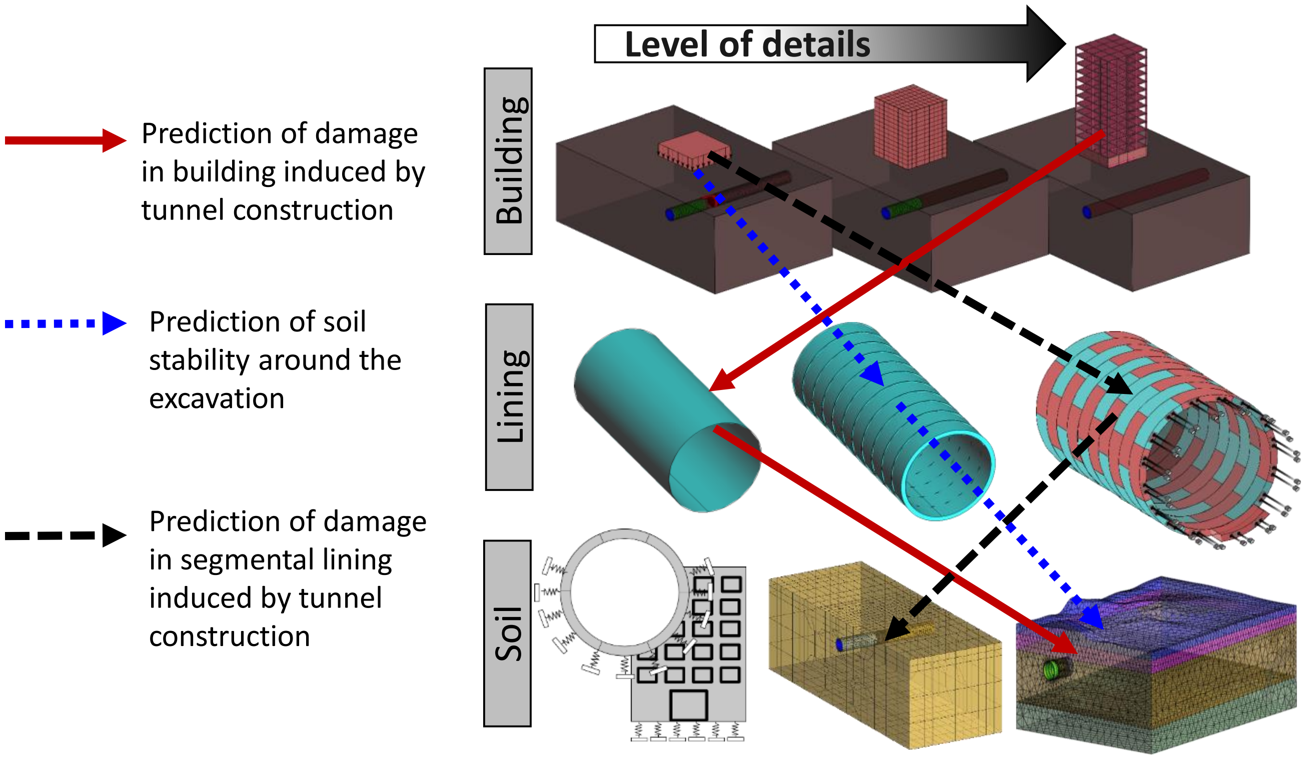


Figure 19 Alternatives for selection of LoDs for individual components based on analysis objectives. Reproduced from (Ninić et al., 2020).

3.4 Geometrical and numerical modelling

Tunnel design assisted by numerical modelling often involves the construction of 3D models (2D models can be acceptable in certain circumstances), consisted of the structures and the ground. Machines, such as a TBM, used to excavate can also be modelled to simulate the machine-ground interaction as detailed in (Zhao et al., 2012). The geometrical models are traditionally generated in a CAD application software and imported to the numerical modelling software, or directly built in the numerical modelling software. Numerical simulation is performed to identify safety concerns and design inadequacy. Under soil conditions, the surface settlement is often the main safety concern, whereas geological structure induced instability is more related to tunnelling through rock mass. Therefore, numerical models established for rock tunnel simulation should always encompass major geological structures. Another concern of underground construction demanding numerical simulation is the deformation of large-span caverns (created to accommodate underground stations, i.e., integral part of a tunnel infrastructure), with their formation similar to conventional tunnelling, characterised by separate excavation and support installation procedures.

BIM-based design can effectively moderate the computation and data sourcing processes for numerical simulation by leveraging the already-established geometrical BIM components (Alsahly et al., 2020). For example, Ninić et al. (2019); Ninić et al. (2017); Ninić et al. (2020) demonstrated the use of a unified numerical and information modelling platform named SATBIM, which is consisted of 1) multi-level tunnel information modelling using Autodesk Revit and Dynamo; 2) geometrical model and finite element mesh generation applying the pre/postprocessor; and 3) numerical analysis employing a process-oriented numerical framework for high-performance computing, as shown in Figure 20. The platform allows the automatic instantiation and execution of numerical model based on the BIM model and visualisation of the numerical simulation results in the BIM environment. The source code of SatBimModeller can be obtained from https://github.com/satbim.

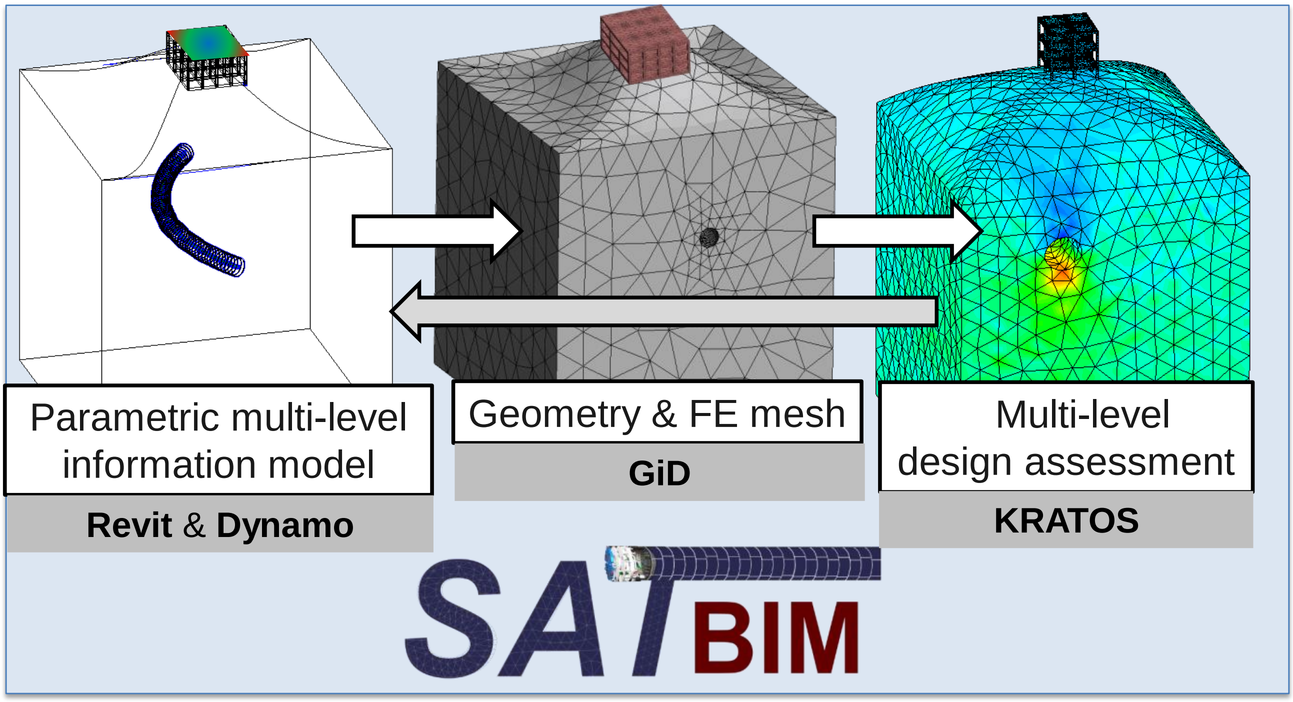
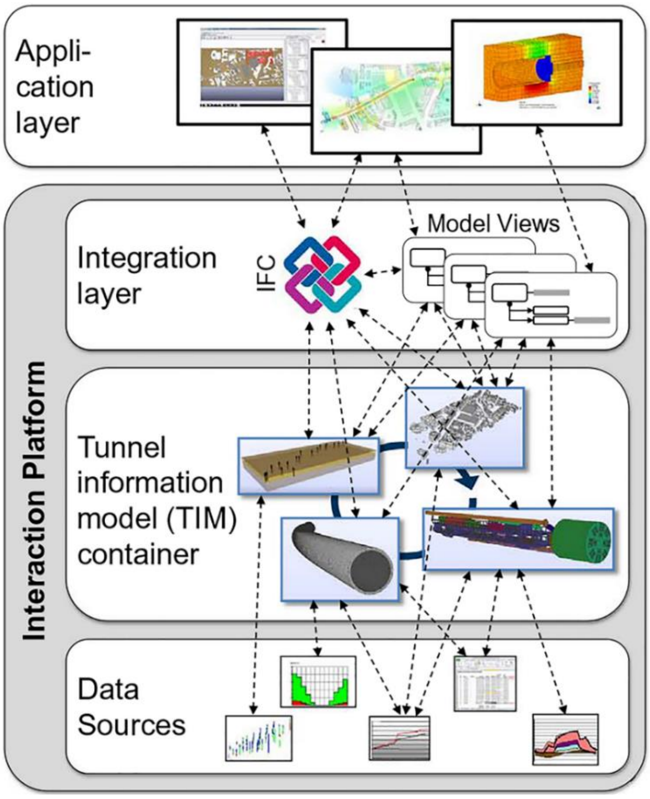


Figure 20 A modelling platform (SATBIM) developed for simulating interactions in tunnelling based on a multi-level design. Reproduced from (Ninić et al., 2020).

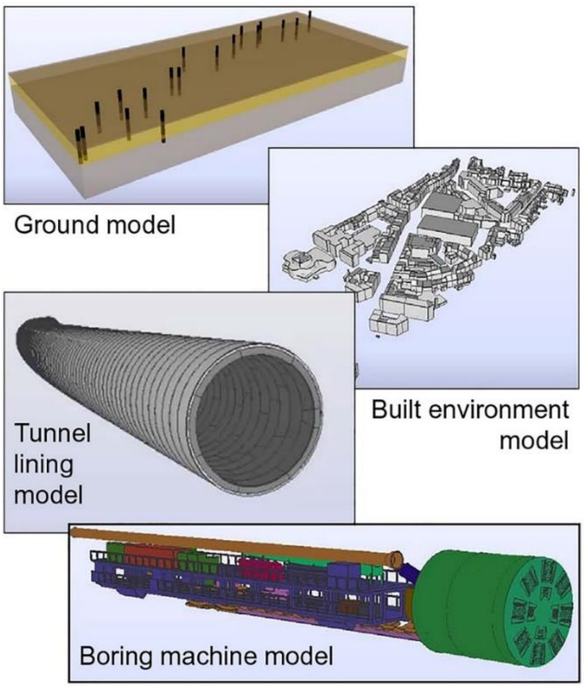
3.5 Multi-components interactive platforms

A multi-components interactive platform can be defined as a service platform consisted of different functional systems. One example is proposed by Koch et al. (2017), as illustrated in Figure 21. Included are an interactive platform designed to aggregate data sources, a tunnel information model (TIM) container consisted of models representing ground, TBM, tunnel and built environment, and an integration layer. Finally, the application layer underpinned by IFC-based access allows applications such as visualisation and numerical simulation to gather relevant data from the TIM container and provides analysis to its users.

Similarly, Zhu et al. (2017) introduced the infrastructure Smart Service System (iS3) that integrates data acquisition and analysis with tunnelling services by combining software and hardware. A range of modules is developed to incorporate geospatial engineering, high-precision modelling and stability analysis. From the application point-of-view, the integrated platform facilitates data management and decision-making efficiency and provides both downloadable and web-based versions of the product. An example of engineering application of iS3 is the prediction of excavation in the Ningbo subway station (Tang et al., 2020). More information about this system can be found on https://github.com/iS3-Project.



(a)



(b)

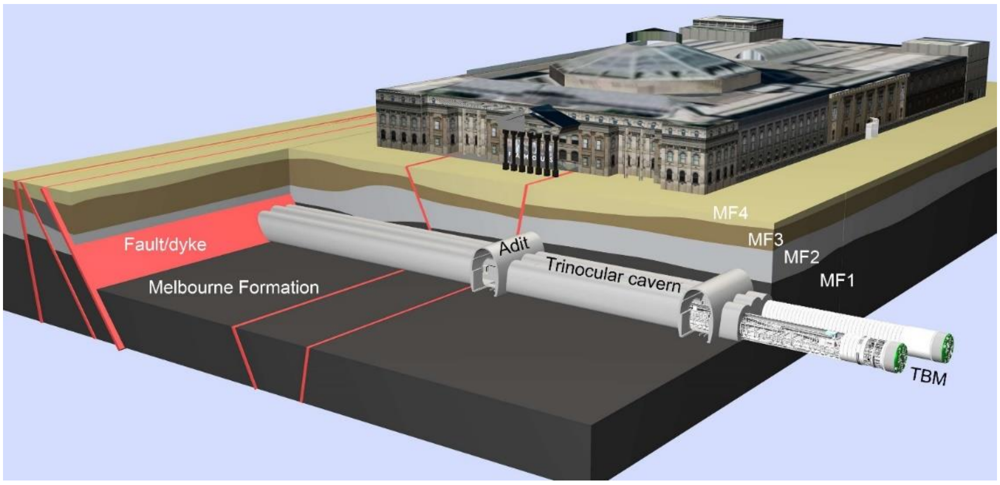
Figure 21 (a) An interactive platform developed for tunnel information modelling and (b) subdomain models contained in the tunnel information model (TIM). Reproduced from (Koch et al., 2017)

To summarise and identify gaps of BIM-based model establishment for underground construction (mainly includes tunnels and underground stations), Table 2 is prepared. A general observation is that a wide range of components has already been covered by existing research. However, owing to the lack of standardisation, the model LoD definitions are prone to ambiguities. In addition, the existing ground models are generally for tunnelling in soil mass that is absent of geological structures, and thus are inappropriate to be implemented in rock tunnel simulation.

Table 2 Examples of existing models by components for shield/TBM tunnelling.

Ground model	Building model	Stations	TBM	Tunnel alignment	Segmental linings	References
					✓	(Yabuki, 2009; Yabuki et al., 2013a)
			✓			(Hegemann et al., 2012)
				✓	✓	(Borrmann and Jubierre, 2013)
				✓	✓	(Vilgertshofer et al., 2016)
✓	✓		✓	✓	✓	(Koch et al., 2017)
✓	✓		✓	✓	✓	(Ninić et al., 2019; Ninic et al., 2017; Ninić et al., 2020)
✓	✓	✓	✓	✓		(Gueulet and Milesy, 2018)
				✓	✓	(Zhong et al., 2018)
					✓	(Zhou et al., 2018)

To address the identified gaps and conform to discussions made in the above sections, a model is proposed taking the Metro Tunnel Project in Melbourne as an example (Figure 22a) consisted of the building (Victoria State Library), ground with geological structures, tunnel related structures, underground stations and TBM. The models are established based on the LoD concept (Figure 22b). For example, the station model at LoD 4, apart from the main structure, will also contain structural support, the shotcrete (as temporary support), rock bolts, canopy tubes and columns to facilitate numerical simulation of interaction (Figure 22c).



(a)

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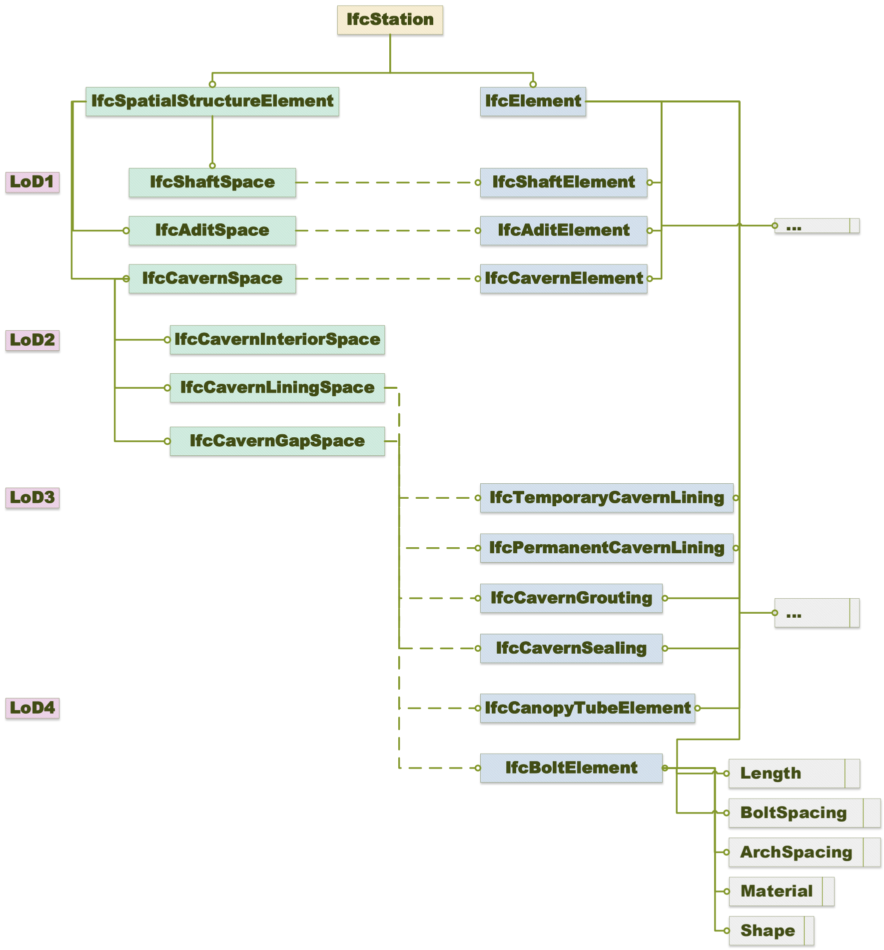
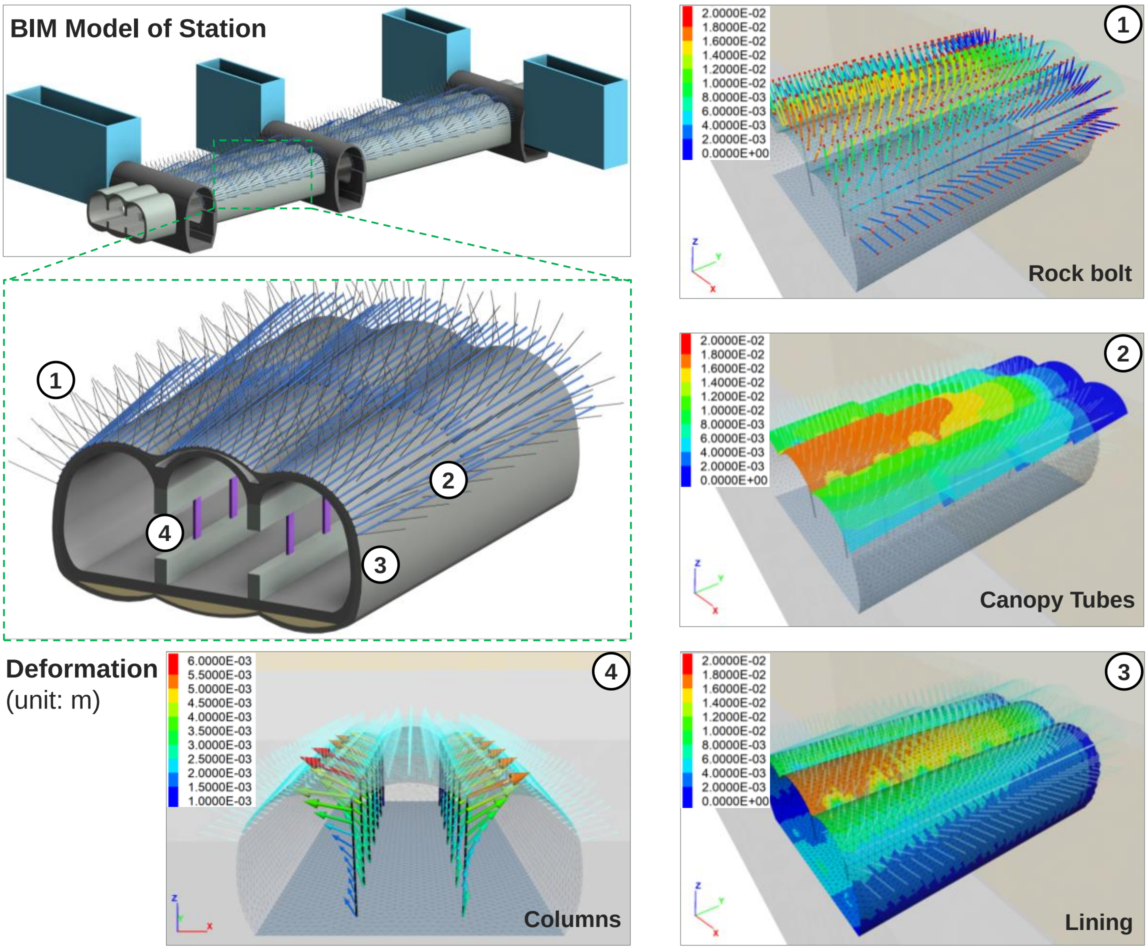


IfcStation
IfcSpatialStructureElement
IfcElement
LoD1
IfcShaftSpace
IfcShaftElement
IfcAditSpace
IfcAditElement
...
IfcCavernSpace
IfcCavernElement
LoD2
IfcCavernInteriorSpace
IfcCavernLiningSpace
IfcCavernGapSpace
LoD3
IfcTemporaryCavernLining
IfcPermanentCavernLining
IfcCavernGrouting
...
IfcCavernSealing
LoD4
IfcCanopyTubeElement
IfcBoltElement
Length
BoltSpacing
ArchSpacing
Material
Shape

774 (b)



(c)

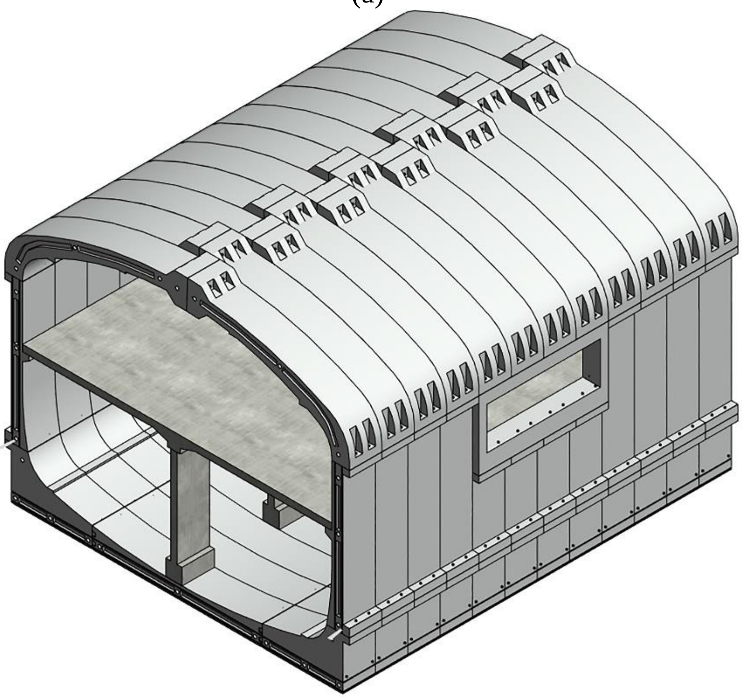
Figure 22 (a) Schematic of an integrated 3D model of the building (State Library of Victoria), ground, tunnel, station and TBM of Melbourne metro. (To visualise the multi-components, the scale and locations of buildings are slightly different from the site.), (b) multi-component BIM model at different levels of IFC for the underground station, and (c) numerical modelling of shotcrete (as temporary support), rock bolts, canopy tubes and columns performed at LoD 4 to assist construction.

3.6 Some innovative construction technologies

This subsection considers the contemporary design and construction techniques emerged in tunnelling and underground construction, including prefabricated construction and non-circular TBMs (ENAA, 2019; Hanshin Expressway, 2020; Li, 2017; Yang et al., 2019) that can also be using BIM for the digital representation of their physical and functional characteristics, but each of them individually is associated with unique features to warrant considerations.

Modularisation or prefabricated construction refers to the practice of assembling large building components at the manufacturing site and transporting the assemblies to the construction site where they are to be installed. Prefabricated technologies have been widely adopted in underground construction since it provides excellent benefits to enhancing safety, quality and efficiency. TBM tunnel space sustained with segmental rings consisted of prefabricated concrete segments is a form of underground engineering that engages prefabricated technology. Unlike tunnels that can detour to avoid unfavourable ground conditions and be built at a certain depth, underground stations are often constructed in densely populated regional centres and at shallow depth prone to create a ground disturbance. Prefabricated technology provides an alternative construction strategy for the construction of underground stations. With structures pre-assembled, the construction period can be greatly reduced, and thus facilitating settlement control and fast road reinstatement. An example of such prefabricated underground station (Changchun Metro line 2) is shown in Figure 23 consisted of a photograph taken onsite when the main structure is completed (Figure 23 a) (Yang et al., 2019) and its BIM model (Figure 23 b).

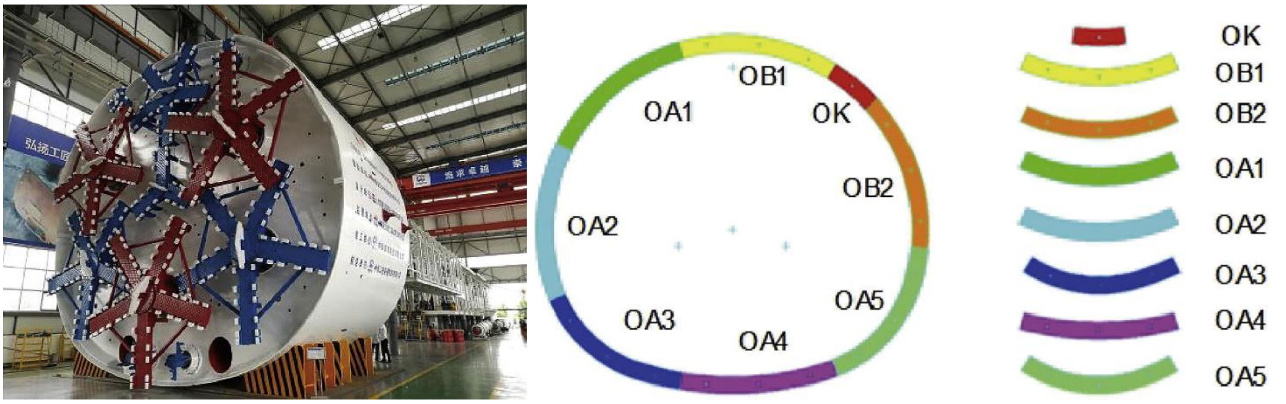
(a)



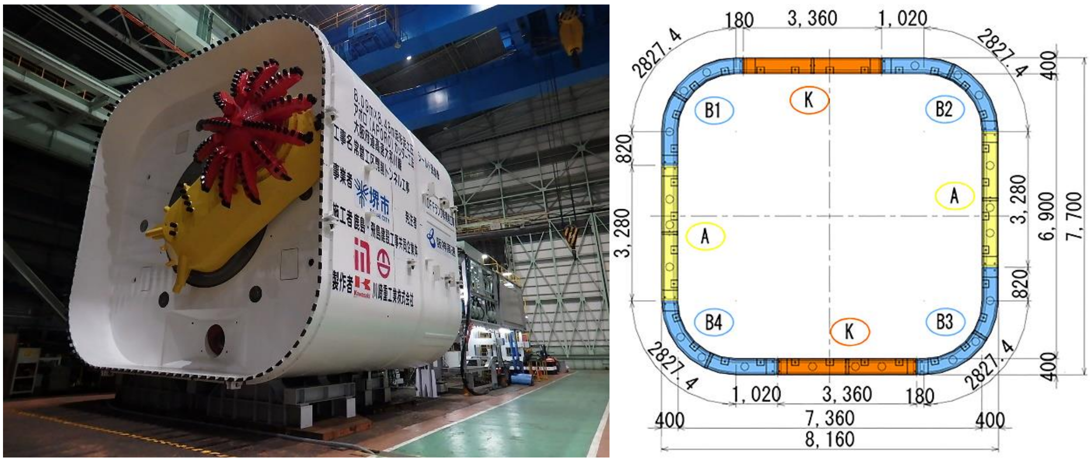
(b)

Figure 23 (a) Photo taken after completion of the main structure of prefabricated underground station on Changchun Metro line 2. Reproduced from (Yang et al., 2019), (b) BIM model for this station (Courtesy of Fang Lin and Xiuren Yang for providing the CAD files and construction information)

Non-circular TBMs and shield machines such as double-O-tube, multi-circular face, rectangular, and horseshoe-shaped TBMs have been employed in creating cross-sections for the development of fit-to-purpose underground space (ENAA, 2019; Hanshin Expressway, 2020; Li, 2017). The horseshoe-shaped cross-sections are advantageous over conventional circular cross-sections in terms of higher utilisation ratio and better mechanical behaviour (Figure 24a). Variations of Kawasaki's APORO Cutter can excavate differently shaped sections, and for example, the rectangular one (Figure 24b) is for Tokiwa work section of Hanshin Expressway Yamatogawa route (Hanshin Expressway, 2020). The erection, installation and bearing capacity of segments are the key technologies involved in non-circular TBMs. The geometrical irregularity of segments used to form a ring may increase the probability of segment dislocation, which requires a higher degree of precision control in segment transport and installation (erection operation) to facilitate the automation of this process.



(a)



(b)

Figure 24 (a) Horseshoe-shaped TBM (left) and segmental rings (right). Reproduced from (Li, 2017); (b) APORO rectangular shield machine (left) and segmental rings (right). Reproduced from (Hanshin Expressway, 2020)

4. Machine learning and computer vision in underground construction

Sensing technologies have been extensively adopted in underground construction for a variety of applications, including geological abnormality prediction, stability and structural health monitoring, and as-built quality control. Traditional geotechnical underground sensing and monitoring engages instruments such as strain gauges, load cells, piezometers, extensometers, inclinometers, and accelerometers for measuring strain, load, pressure, deformation, tilt and vibration, respectively (Iskander, 2017). Strategies implemented in the tunnel and underground infrastructure maintenance and inspection will not be systematically reviewed, interested readers are referred to Federal Highway Administration (FHAOBS US, 2015) and (Pamukcu and Cheng, 2017) for details. The emerging sensing technologies leverage advances in both hardware and software to create monitoring systems embedded with improved communication efficiency and information richness.

During tunnelling and post-construction operation and maintenance, a significant volume of data is produced through geophysical prospecting and sensing deployment. While machine learning algorithms have been widely applied on data obtained from geo-prospecting (Alimoradi et al., 2008; Pasolli et al., 2009) and machine operation (Benardos and Kaliampakos, 2004; Mahdevari et al., 2014), breakthroughs in the domain of deep learning are increasingly used in combination with traditional computer vision techniques in infrastructure inspection and monitoring (Bao et al., 2019; Koch et al., 2015; Spencer et al., 2019).

The section reviews and provides examples of machine learning and computer vision-based techniques that are broadly applied to underground construction (Section 4.1) and post-construction operation and maintenance (Section 4.2), with Figure 25 schematically depicts a typical workflow. In general, with increasing breadth and diversity of sensor deployment (e.g., TBM's built-in sensors, interferometric Synthetic Aperture Radar (InSAR), ground-penetrating radar (GPR), imaging, and laser scanning), a large volume of data will be acquired that is interpretable by machine learning and computer vision-based techniques. Visualisation and manipulation of the analysis assisting evaluation and decision-making tasks (e.g. seismic-event prediction and classification of lining damages) can be achieved by establishing an application layer (e.g. a graphical user interface).

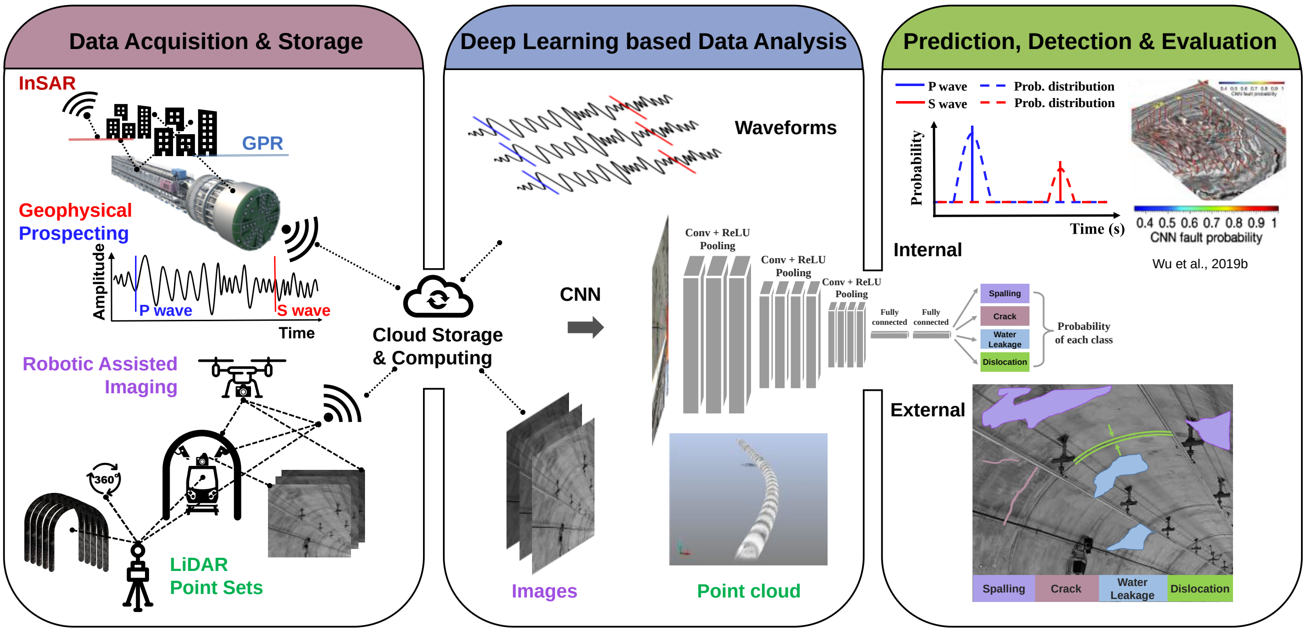


Figure 25 Workflow of data acquisition, analysis and evaluation based on machine learning and computer vision

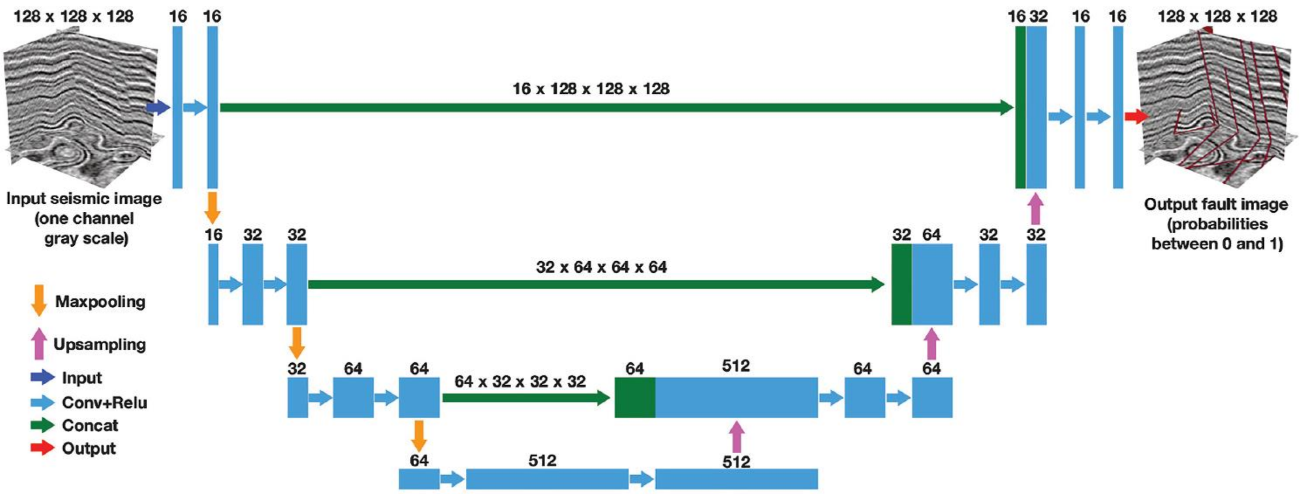
4.1 Construction stage

A large volume of data is produced during the construction stage, that can be broadly classified as from waveform-based geological prospecting (mainly acoustic/seismic wave and electromagnetic wave, i.e. GPR), machine operation, and ground prediction and evaluation. The below subsections will briefly review these sensing methods while examining the applications of machine learning in interpreting the data.

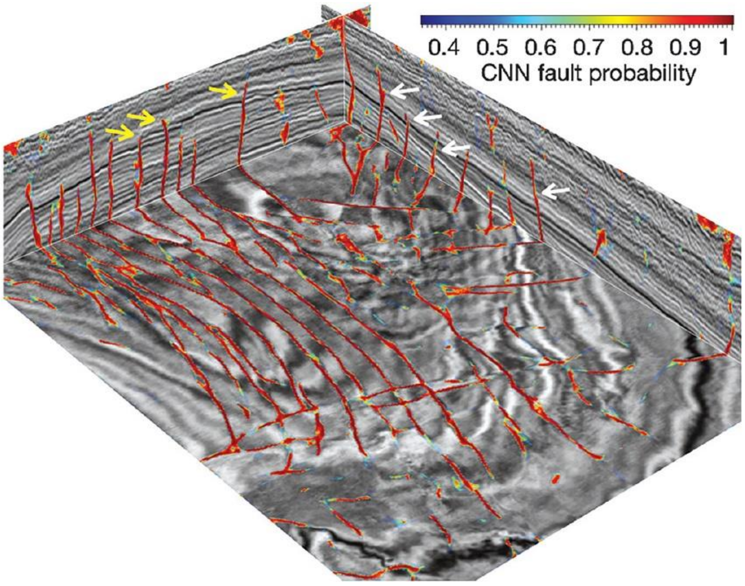
4.1.1 Waveform-based geological prospecting

A range of geological ahead prospecting harnessing geophysical methodologies is applied in tunnelling and underground construction to obtain knowledge of local geological conditions. A thorough review of the technological principles and applications of geophysical ahead prospecting methods to tunnelling can be found in (Li et al., 2017).

Full-wave inversion plays a vital role in subsurface characterisation, which has been considered by (Wu and Lin, 2018) proposing the InversionNet, a data-driven model that learns a mapping from seismic waves to the subsurface velocity models. For detecting geological discontinuity such as faults and dykes, seismic-wave based methods are commonly used in both drilling-and-blasting (Alimoradi et al., 2008) and TBM tunnels (Yokota et al., 2016). Seismic waves are generated by using explosives, hammers or vibration sources with sensors installed on the tunnel face, sidewalls, TBM shields or on the surface. Seismic methods distinguish different rock types based on the time contrast for waves to be reflected due to lithological discontinuities. ANNs have been employed to predict weak geological zones during the construction of a water supply tunnel by deducing a relationship between the TSP-203 (Tunnel Seismic Prediction) (Amberg, 2002) resulted seismic properties and those of RMR (rock mass rating) (Alimoradi et al., 2008). Wu et al. (2019b) proposed to train 3D synthetic data sets of seismic images using supervised fully CNN simplified from U-Net (Ronneberger et al., 2015) that consists of a contracting path for context capturing and a symmetrical-expanding path for localisation (Figure 26). The fault detection is treated as a binary image segmentation problem of labelling images with ones on faults and zeros elsewhere, and a balanced cross-entropy loss function can be used.



(a)



(b)

Figure 26 (a) A simplified U-Net structure proposed for 3D fault detection, and (b) detected fault and fault likelihood based on the CNN model. Reproduced from (Wu et al., 2019b).

Microseismic (MS) mainly functions to assess rock mass stability and predict hazardous rockburst in both hard rock and coal. Rocks and most of brittle solids emit low-level acoustic or seismic signals when they are stressed (Hardy, 2003); therefore, MS monitoring systems deployed underground can precisely locate the seismic source through signal interpretations and incorporate adequate ground control in a timely manner to help improve excavation safety. The resulted signal waveforms can be used in training neural networks for pattern recognition and feature extraction, as shown in Figure 27 (Kong et al., 2018). Another example can be found in (Zhu and Beroza, 2019), which proposed a deep neural network algorithm, named the PhaseNet, that is fed with three-component waveforms to predict the probability distributions of P-wave, S-wave, and noise. Huang et al. (2018b) employs CNN in a method developed for identifying the Time Delay of Arrival taking cross-wavelet transform power and phase as inputs, and subsequently locating the MS events.

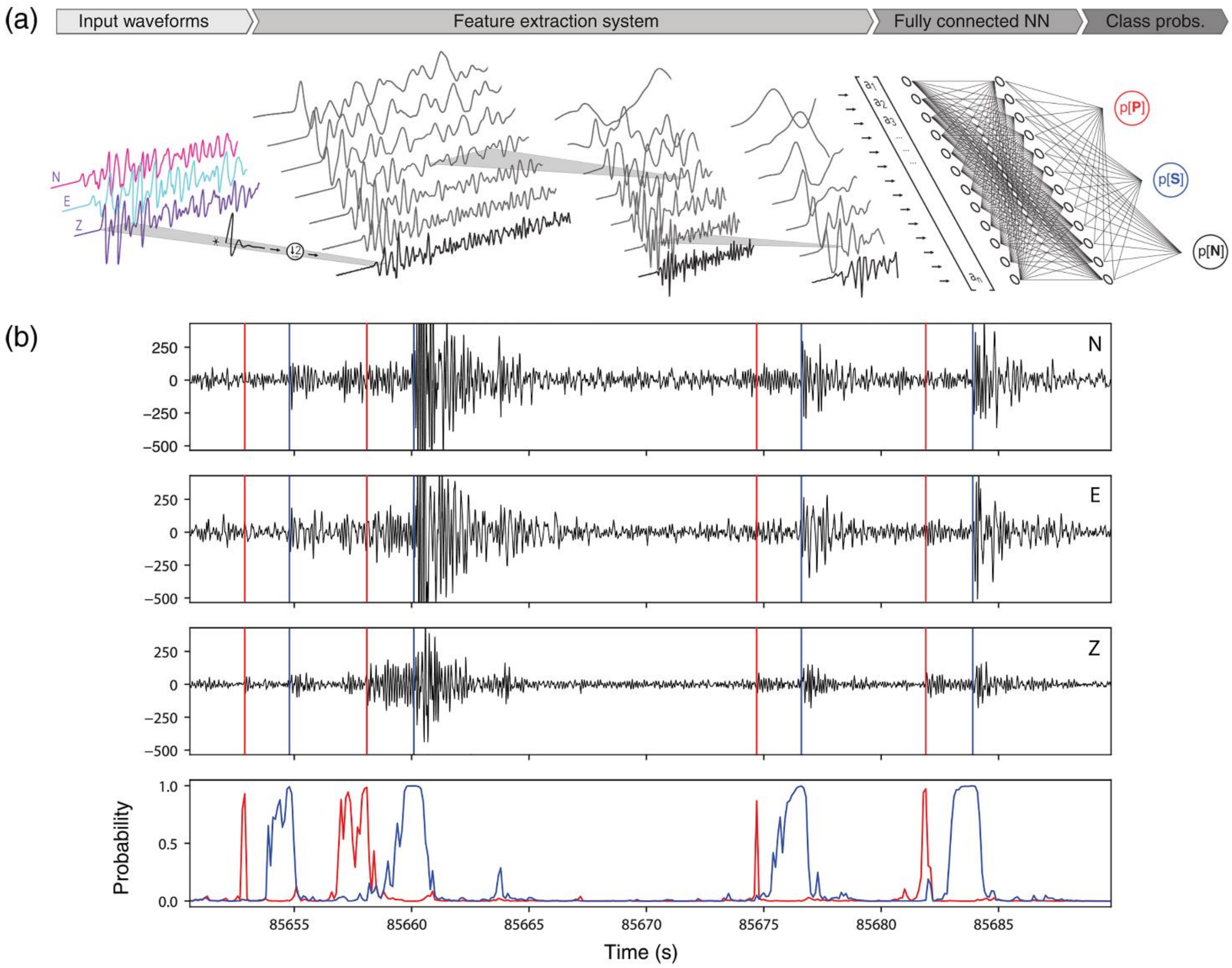
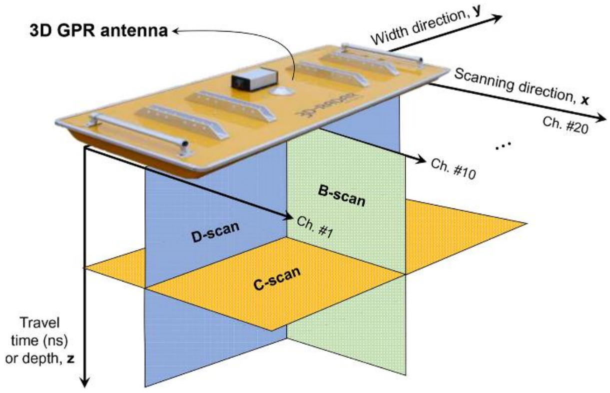


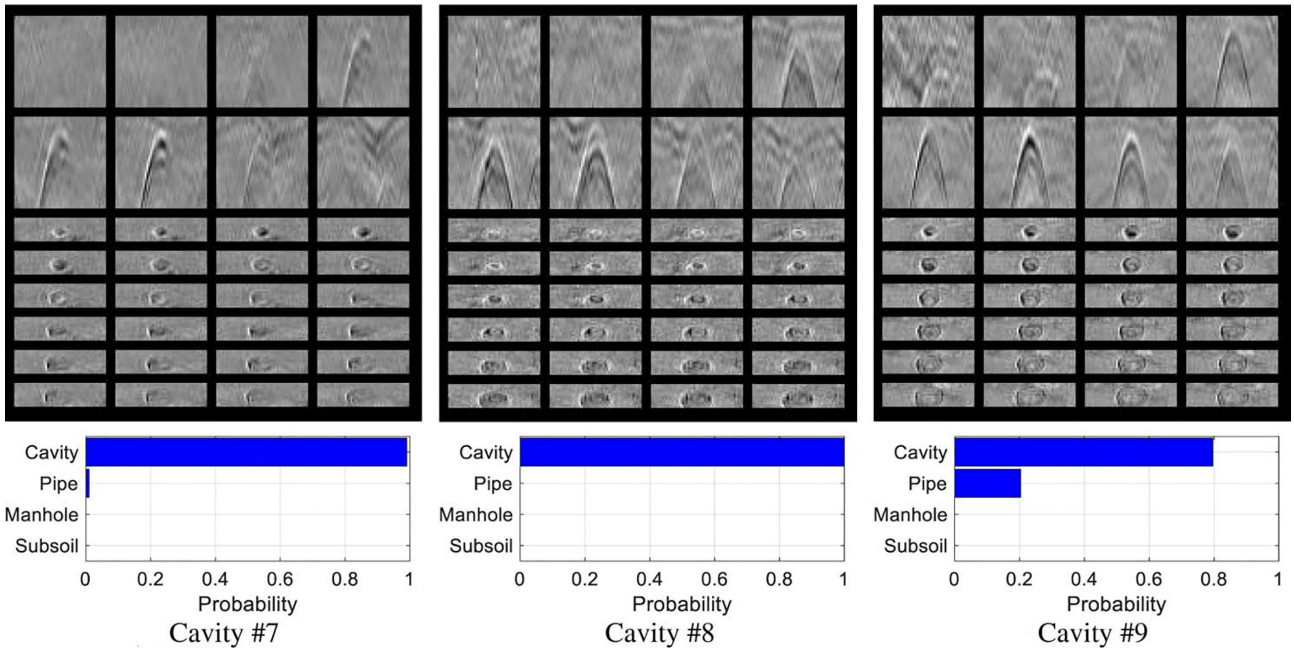
Figure 27 (a) A cartoon schematic illustrating CNN for the generalised phase detection (GPD), a new category of earthquake detection algorithms that trains CNN to learn generalised representations of seismic waves from a substantial number of seismograms. The CNN feature extraction system operates in combination with fully connected neural network to produce class probabilities for noise, P and S waves. (b) An application example of GPD to waveforms obtained from a seismic event. Red and blue colours indicate P and S waves, respectively. Reproduced from (Kong et al., 2018).

Before carrying out additional excavation, identification of existing underground infrastructure and utility network is required for the efficient planning and management of underground space. Driven by the land shortage, countries with limited national terrestrial areas such as Singapore and UK have initiated programmes dedicating efforts into digitalising underground space by mapping and assessing the built infrastructure such as utilities to create 3D shareable model (Metje et al., 2007; Schrotter and van Son, 2019). This starts with capturing data on the ground surface using conventional surveying tools such as geophysical techniques like GPR (Van Son et al., 2018).

GPR based on electromagnetic methods is a useful tool to identify alien substances or discontinuities by detecting signal attenuation of the backscattered radiation from targeted objects (Daniels, 2004; Wai-Lok Lai et al., 2018). Pasolli et al. (2009) proposed a pattern-recognition system involving pre-processing to reduce noise, followed by feature extraction and finally an SVM classifier for the identification and classification of buried objects from GPR imaging. Reichman et al. (2017) discussed employing and comparing three CNN configurations for detecting buried threats and concluded that detection performance can be improved by pretraining and dataset augmentation. Moreover, Kim et al. (2019) proposed to train a deep CNN on multichannel 3D GPR data of both B-scan and C-scan images for underground object classification (Figure 28).



(a)



(b)

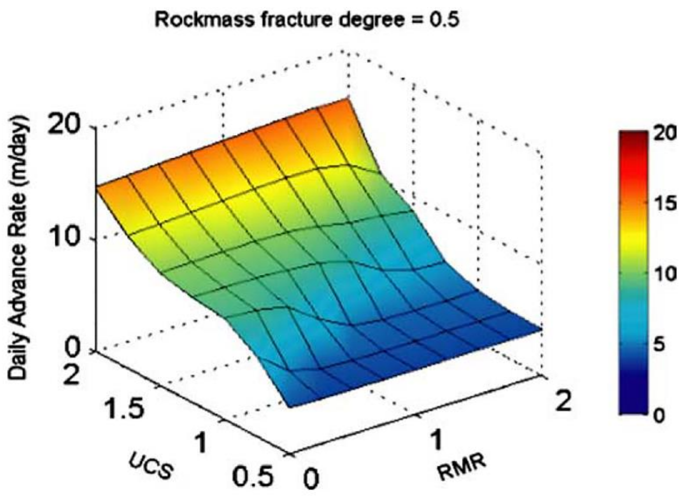
Figure 28 (a) Illustration of orthogonal slice planes of 3D GPR data; (b) cavity (cavity, pipe, manhole, subsoil) classification probabilities produced by a CNN method with the 3D GPR data (grid image). Reproduced from (Kim et al., 2019).

Along with being employed for above-surface surveying for already laid utility networks, GPR is also used in ahead geological prospecting in tunnelling. The contrast in electromagnetic properties of geological heterogeneity such as groundwater, faults and fractured rock can be detected and depicted by GPR when the image is examined by analysts. However, condition differentiation and severity evaluation of GPR images are highly dependent on the analyst's experience and are varied case by case (Abouhamad et al., 2017). The database containing GPR imageries can form an essential part of a management system to enable collaborative interpretation and decision-making based on functional visualisation. An example of such visualisation platform can be found in (Wei et al., 2019) where a back-end database containing data acquired onsite using GPR and seismic methods is used for expert interpretation to obtain geological insights as well as an imagery evidence base. With the establishment of such database, deep neural networks can be applied to extract features and learn patterns. An example is found in (Liu et al., 2019), which introduced a deep neural network architecture for mapping GPR data to permittivity maps and has been applied to reconstruct tunnel lining defects. Apart from the above examples, a review on the applications of ANN and machine learning techniques to GPR can be found in (Travassos et al., 2018).

Besides GPR, water-bearing bodies can also be uncovered by using electrical resistance tomography (ERT) by measuring the apparent electrical resistivity structure ahead of the tunnel face. ERT combines the technology of traditional electrical probing with tomography inversion to reconstruct the image based on the calculated subsurface distribution of electrical resistivity from extensive resistance measurements (Daily et al., 2004). Deep learning techniques have been applied for ERT image reconstruction, such as in (Chen et al., 2020; Tan et al., 2018).

4.1.2 TBM performance

Machine learning has been broadly used on machine operational data, especially in TBM tunnelling, such as cutting force, thrust load, cutter torque and penetration, mainly for two purposes: predict TBM performance and forecast geological conditions. The prediction of TBM performance utilising machine learning algorithms on embedded-sensor data has been widely studied (Alvarez Grima et al., 2000; Benardos and Kaliampakos, 2004; Erharter and Marcher, 2020; Liu et al., 2017b; Mahdevari et al., 2014; Marcher et al., 2020; Mokhtari and Mooney, 2020; Salimi et al., 2019; Salimi et al., 2016; Xu et al., 2019; Yoo and Kim, 2007). For example, Benardos and Kaliampakos (2004) developed a model for predicting TBM advance rate by employing an ANN for determining the influence of parameters such as RQD on TBM performance. Figure 29(a) shows the surface plot of the proposed model predicting the advance rate with respect to RMR and UCS (uniaxial compressive strength) for a given RQD. Mahdevari et al. (2014) have developed a TBM penetration rate (PR) prediction model based on SVM algorithm with the predicted values closely approximate measured values as shown in Figure 29(b), where the dashed line represents the line of equality. In addition, ANN-based tunnelling performance prediction has been integrated into the GIS platform harnessing its data management and visualisation capability to improve decision-making for routine tunnel design works (Yoo and Kim, 2007). Besides supervised machine learning methods, unsupervised approaches have also been applied in analysing TBM monitoring data during tunnel construction. For example, Zhou et al. (2019a) proposed to integrate spectral clustering and complex network theory for shield tunnelling machine monitoring data based on multi-dimensional datasets. The classification results were analysed to infer the geological condition adaptability and cutter maintenance of the shield machine. Gao et al. (2019b) applied three types of RNNs (i.e., traditional RNN, LSTM network, and GRU: gated recurrent unit network) to predict the real-time operating parameters (i.e., the torque, velocity, thrust and the pressure of chamber) based on *in-situ* operating data, as shown in Figure 29(c) Moreover, deep learning techniques have also been applied in predicting the position of tunnelling machines to foster construction quality and update as-built information. Zhou et al. (2019b) proposed an integrated deep learning model consisting of the wavelet transform, CNN, and LSTM for predicting the attitude and position of the shield machine.



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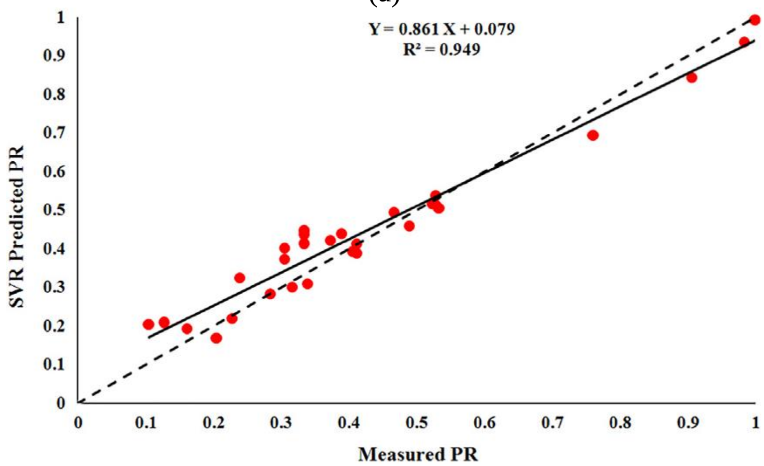

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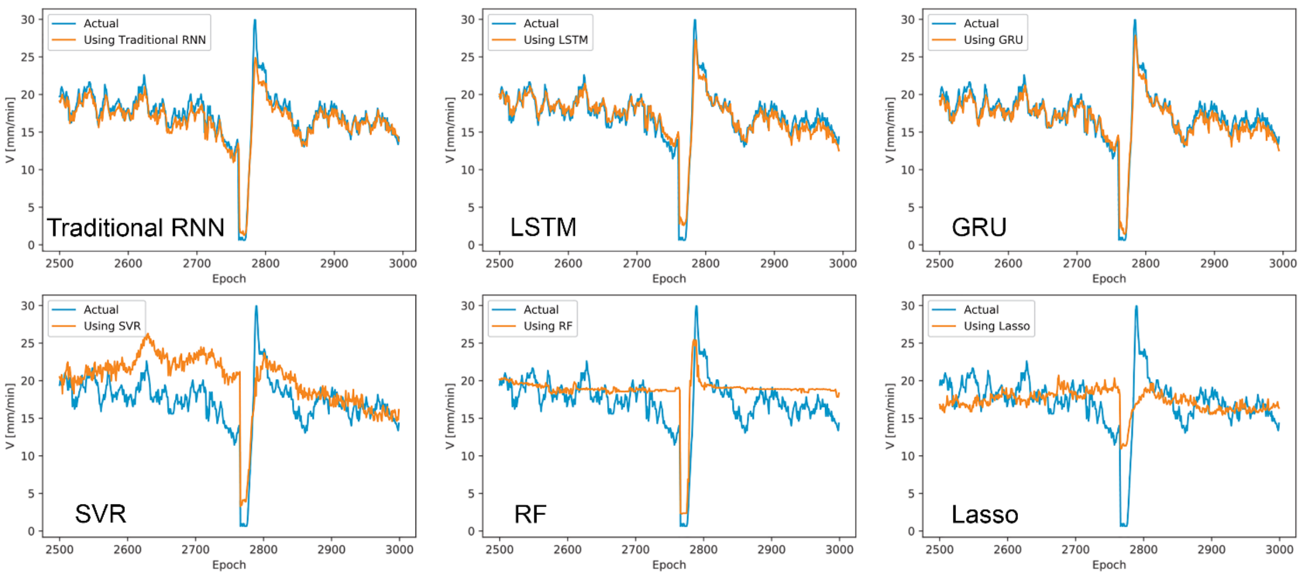
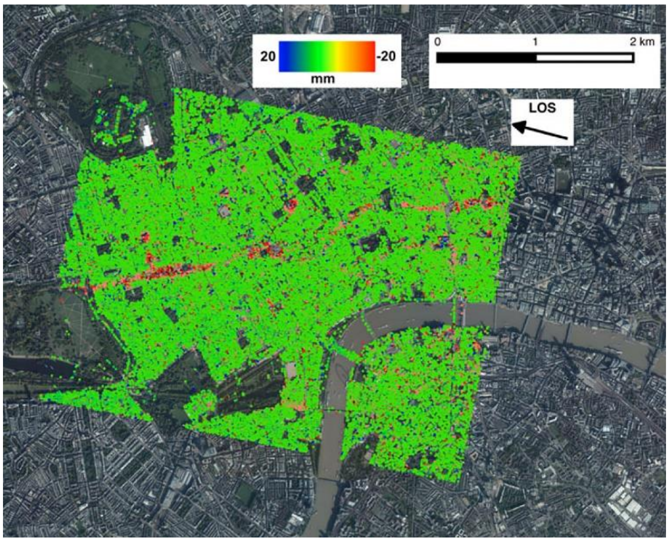


(c)

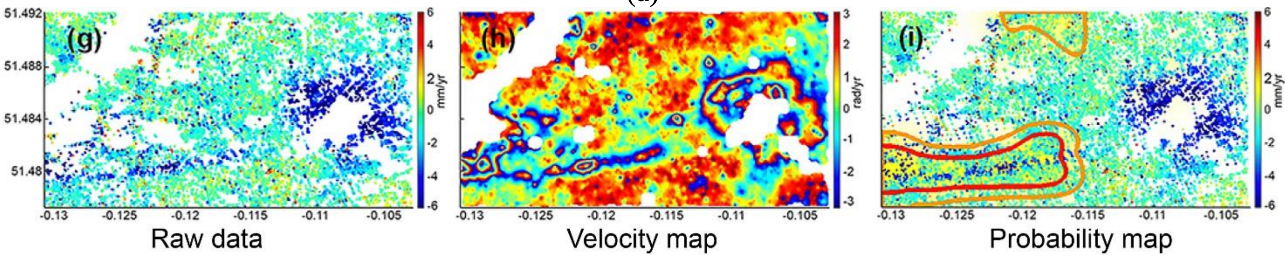
Figure 29 (a) A surface plot of an ANN model developed for predicting TBM advance rate based on influence parameters, the monograph is constructed in relation with the RMR and UCS parameters for a given RQD value of 0.5. Reproduced from (Benardos and Kaliampakos, 2004), (b) Graphical output provided by regression analysis for the normalised testing data. Reproduced from (Mahdevari et al., 2014), (c) real-time prediction of TBM operating parameters using three RNNs and three classical regress models (SVR: support vector regression, RF: random forest and Lasso). Modified from (Gao et al., 2019b).

4.1.3 Ground prediction and evaluation

The ground deformation induced by underground construction mainly includes the convergence of the tunnel wall, the settlement at the ground surface, and the damage assessment of existing structures. Machine learning algorithms have been widely applied for the prediction of surface settlement induced by TBM tunnelling (Ninić and Meschke, 2015; Suwansawat and Einstein, 2006; Zhang et al., 2020a; Zhang et al., 2019b) and evaluation of geological conditions (i.e., strength, crack frequency and weathering) of tunnel faces (Tsuruta et al., 2019). Traditionally terrestrial measurement techniques may introduce interruptions to the construction process and are time and material consuming (Kavvadas, 2005; Lunardi, 2008). With the increased power of remoting sensing techniques, InSAR enables the accurate measurement of tunnelling-induced change detection, 4D mapping and environmental monitoring with millimetre accuracy in near-real-time (Barla et al., 2016; Moreira et al., 2013; Rucci et al., 2012). Typical examples of applying InSAR include monitoring and assessment of ground settlement (Schindler et al., 2016), landslide deformation (Bayer et al., 2017) and building damages (Giardina et al., 2019) induced by tunnelling. Moreover, Schindler et al. (2016) proposed a 4D BIM concept for visualising settlement data and incorporating TBM performance parameters (thrust force) in a 3D VR environment. Research efforts have been primarily made on improving the methods and capacities of processing the large volume of images, while information accuracy is heavily relied on manual inspection and expert interpretation. An example of research aims to address this can be found in (Anantrasirichai et al., 2020), where a CNN-based framework is developed to automatically detect the ground deformation induced by coal mining and tunnelling (London-Northern line extension) using high-resolution InSAR images (5 m/pixel) and UK velocity maps (2015-2019), as shown in Figure 30. Zhu et al. (2020) conducted a comprehensive review of the recent advances and existing benchmark datasets in the utilisation of different deep learning techniques on various SAR applications.



(a)



(b)

Figure 30 (a) InSAR-Cumulative displacement map over London during April 2011-December 2015 with negative values indicating the ground settlement above the Crossrail twin tunnels (LOS: the satellite line of sight). Modified from (Giardina et al., 2019); and (b) CNN-based detection of London – Northern line extension (g. raw data; h. the wrapped and interpolated velocity map, and i. probability map overlaid on the raw data, and the brighter yellow shows the higher probability.). Reproduced from (Anantrasirichai et al., 2020)

Machine learning algorithms are also applied to predict geological conditions based on TBM operating parameters (Erharter and Marcher, 2020; Liu et al., 2020; Zhang et al., 2019a). Zhang et al. (2019a) applied a SVM classifier with an average precision of 98.6% to predict geological conditions of changing rock mass type after compressing big TBM operational data using an unsupervised algorithm. Liu et al. (2020) have developed a hybrid algorithm which integrated ANN with simulated annealing for the prediction of rock mass parameters, the distance between the planes of weakness, and the orientation of discontinuities based on TBM driving parameters. Erharter and Marcher (2020); Erharter et al. (2019a); Erharter et al. (2019b) developed an unsupervised machine learning-based framework for TBM data-driven rock mass classification and applied it to predict the TBM performance and rock properties in the Trenner Base Tunnel in Italy.

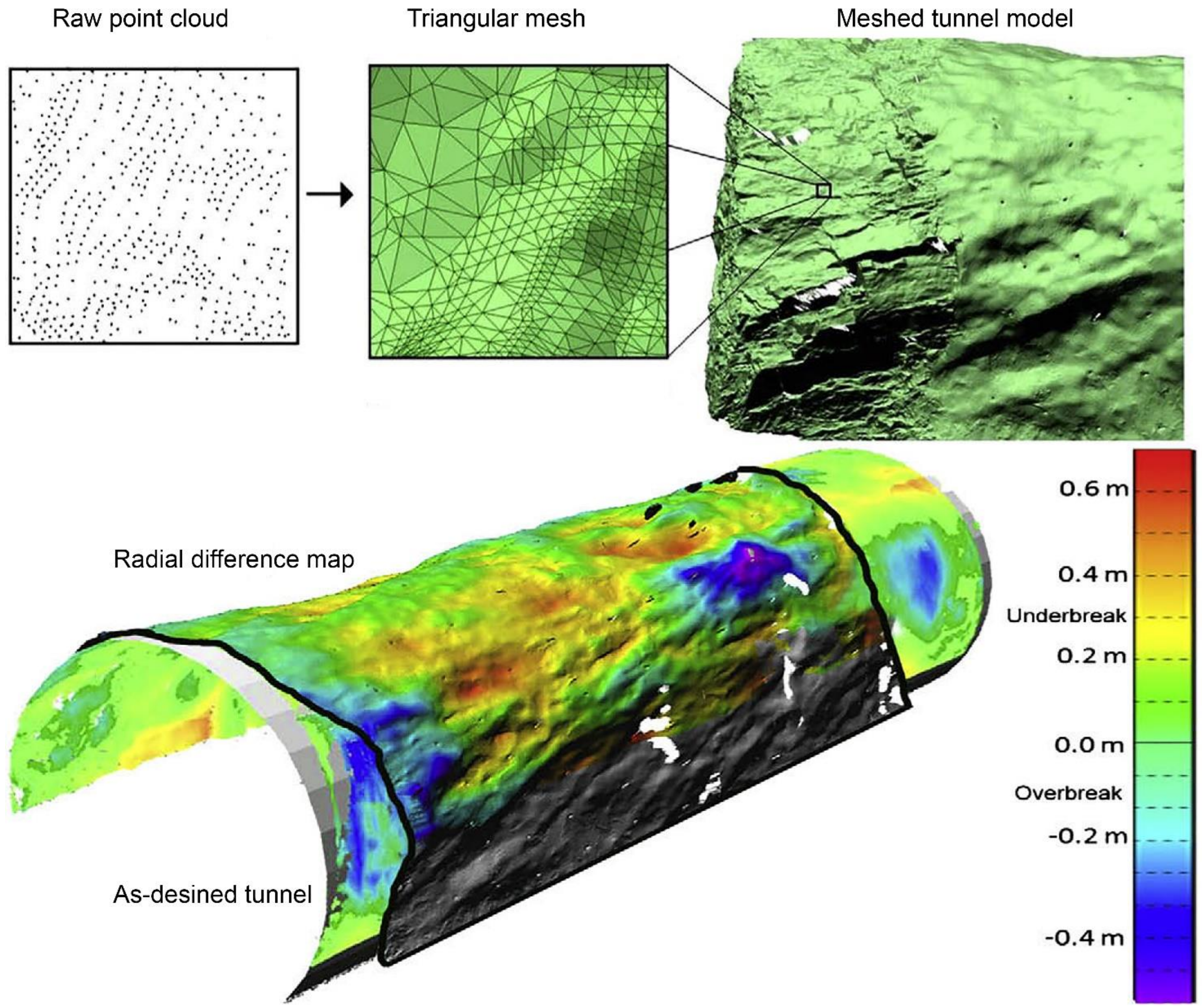
4.2 Operation and maintenance stage

With growing deployment of optical sensors, computer vision and deep learning techniques have been increasingly applied in the general inspection and monitoring of civil infrastructures (Fathi et al., 2015; Feng and Feng, 2018; Koch et al., 2015; Shakhatreh et al., 2019; Soga and Schooling, 2016; Spencer et al., 2019; Ye et al., 2019). Inspection tasks are mainly consisted of two steps: data acquisition and computer vision-based data processing to effectively detect damage and change on the structure surface. Whereas monitoring through the quantitative measurements using sensors such as strain gauges, load cells, and extensometers are useful to obtain an understanding of structural integrity. However, results achieved this way typically have a low spatial resolution or require dense sensor deployment, and thus not necessarily efficient if only occasional monitoring is required (Spencer et al., 2019). Alternatively, vision-based, non-contact monitoring frameworks using photogrammetric techniques can resort for change detection while allowing high maintenance flexibility and spatial resolution. In the following subsections, application examples of machine learning and computer vision for inspection and monitoring of underground construction, especially tunnels, will be examined from the aspect of damage and change detection based on point-sets and images. The discussed algorithms and techniques are environment insensitive, and thus have universal applications to all civil infrastructure; nevertheless, additional lighting may be required for acquiring images in visual degraded environment. These techniques and applications are necessarily developed for improved infrastructure condition assessment and facilitating as-built BIM accuracy.

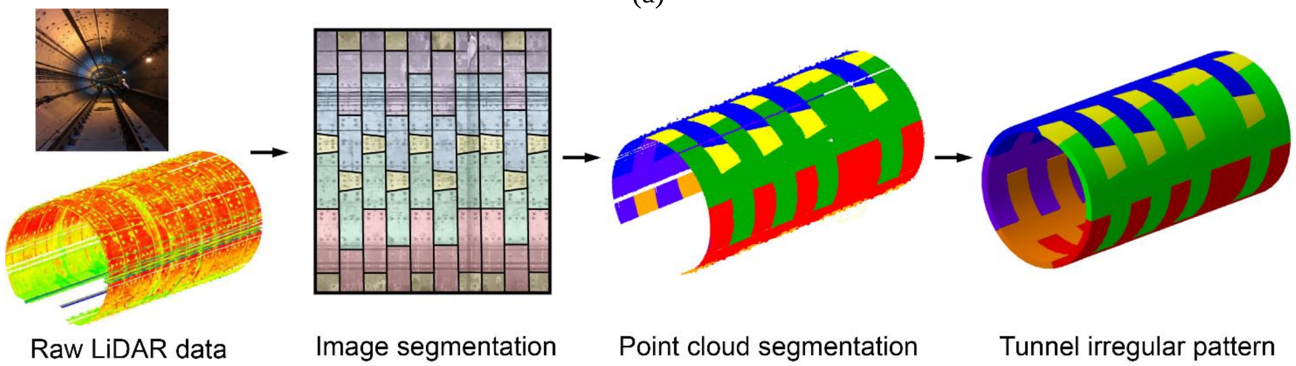
4.2.1 Point sets-based change detection

Terrestrial laser scanning (TLS) and mobile laser scanning (MLS) have increasingly been applied for underground geotechnical applications such as tunnel deformation measurements (Cui et al., 2019; Nuttens et al., 2010; Wang et al., 2014; Xie and Lu, 2017), water leakage (Xu et al., 2018; Yu et al., 2018) and detection of structural discontinuities (Fekete et al., 2010). A point cloud dataset covering the full surveyed area is achievable via an automatic rotation up to 360^{o}. The conversion process from point cloud to a visual representation is applied to provide geotechnical insights, as shown in Figure 31a (Fekete et al., 2010).

Moreover, as-built models based on data acquired by 3D laser scanning have been successfully integrated with BIM (Brilakis et al., 2010; Randall, 2011; Wang et al., 2016; Wei et al., 2018). Based on the image- and geometry-collaborative hierarchical segmentation, Yi et al. (2019) proposed a hierarchical framework to model the tunnel structures from the LiDAR point cloud captured by a TLS. Figure 31b shows the modelling process of the tunnel with a staggered joint pattern. Not only point-clouds data can be reconstructed to as-built BIM models (Cheng et al., 2019; Pärn and Edwards, 2017; Tang et al., 2010), BIM model can also transfer semantic information to point clouds. Czerniawski and Leite (2019) proposed a method for creating large labelled datasets of point clouds by transferring BIM semantics through geometry extraction and point-to-point copying of semantics. The labelled point clouds dataset can then be used for training deep neural networks saving significant manual labelling efforts.



(a)



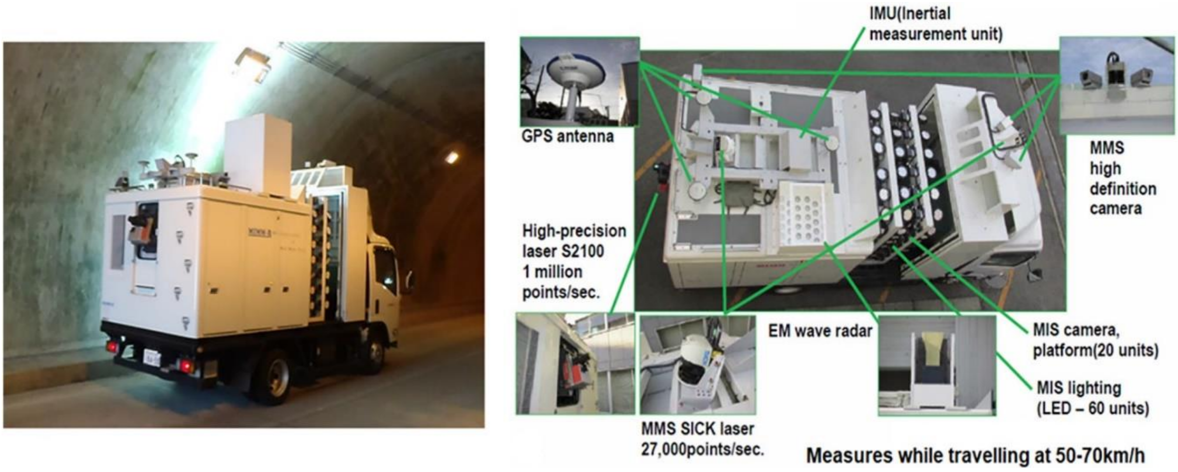
(b)

Figure 31 (a) Procedures involved in processing point-cloud data from raw point clouds to a visual representation for a drill and blast tunnel (final shotcrete profile on the as-designed tunnel profile). Modified from (Fekete et al., 2010), and (b) procedures involved in modelling tunnel with a staggered joint pattern, engaging image segmentation and point cloud segmentation. Reproduced from (Yi et al., 2019).

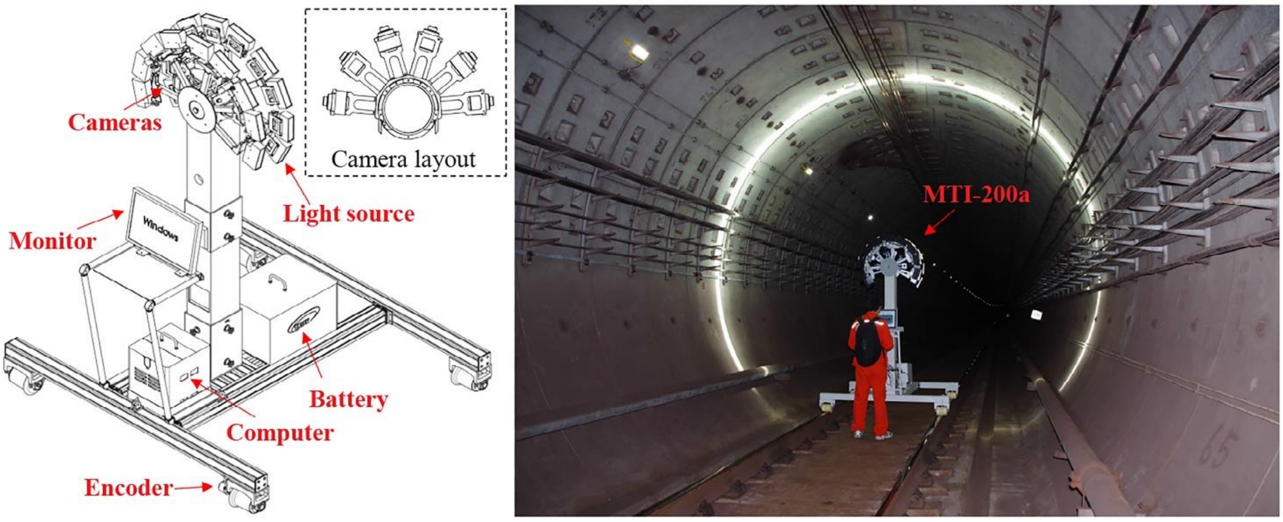
4.2.2 Image-based damage and change detection

Deep learning and computer vision techniques have been widely applied for the general inspection and monitoring of civil infrastructures (Fathi et al., 2015; Feng and Feng, 2018; Koch et al., 2015; Shakhatreh et al., 2019; Soga and Schooling, 2016; Spencer et al., 2019; Ye et al., 2019) that include the detection of structural deterioration such as cracks, spalling and seepage using image data obtained from the inspection (Cha et al., 2018; Cha et al., 2017; Gao et al., 2019a; Huang et al., 2018a; Nash et al., 2018; Ren et al., 2020; Xue and Li, 2018). Specific inspection vehicles and robotic systems equipped with cameras for the acquisition of 2D and 3D profiles of the recorded surface have been engaged in tunnel lining inspection (Attard et al., 2018; Montero et al., 2015). For example, in a review on research and development for infrastructures maintenance in Japan by Fujino and Siringoringo (2020), a high-speed (50-70 km/h) mobile road tunnel inspection vehicle named MIMM-R is described as an integrated mobile platform mounted with the laser scanner, camera and electromagnetic wave radar devices (Figure 32a). In addition, Huang et al. (2018a); Huang et al. (2017) introduced a CCD-camera based rapid damage detection system for railway tunnel structures with images captured by a continuously scanned image acquisition equipment, named Moving Tunnel Inspection (MTI-100/200a) (Figure 32b).

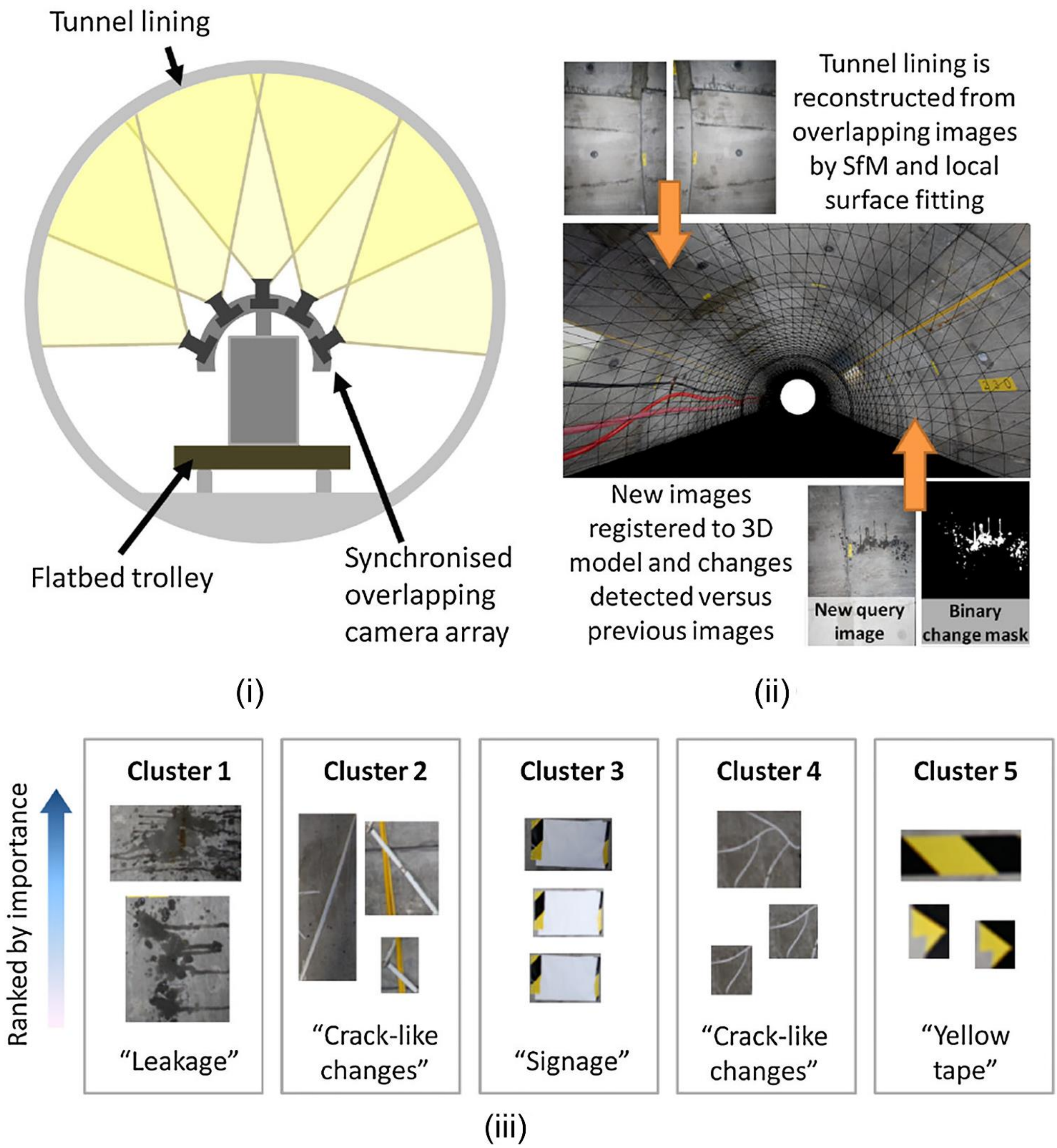
Traditional computer vision methods engaging low- to intermediate-level image processing techniques and conventional machine learning algorithms have been applied to damage and change detection of tunnel. Recent research efforts include using photogrammetric techniques, such as Structure from Motion (SfM), to facilitate 3D scene reconstruction using only 2D images based on the extraction of invariant features from overlapping (Westoby et al., 2012). An example is illustrated in Figure 32(c), where a 3D tunnel surface model is reconstructed from a series of reference images using SfM that allows change detection by accurately localising new images within the model. This forms part of an automated system, producing ranked clusters of detected changes (Stent et al., 2016). Image stitching/mosaicking for the generation of panoramic images are also adopted to facilitate tunnel interior inspection (Kim et al., 2018; Zhu et al., 2016b).


IMU(Inertial measurement unit)
GPS antenna
MMS high definition camera
High-precision laser S2100 1 million points/sec.
EM wave radar
MIS camera, platform(20 units)
MIS lighting (LED – 60 units)
MMS SICK laser 27,000points/sec.
Measures while travelling at 50-70km/h

(a)


Cameras
Camera layout
Light source
Monitor
Battery
Computer
Encoder
MTI-200a

(b)



(c)

Figure 32 Multi-component mobile inspection platform: (a) a high-speed (50-70 km/h) mobile road tunnel inspection vehicle (left) deployed with a range of surveying devices, including GPS antenna, laser scanners, cameras and radars (right). Reproduced from (Fujino and Siringoringo, 2020); (b) a camera-based tunnel inspection equipment enforced with on-board computer and light source. Reproduced from (Huang et al., 2017), and (c) a tunnel lining inspection framework (i. a camera-based tunnel inspection device used to ii. produce overlapping images of tunnel linings. By applying SfM and image registration, surface reconstruction and change detection are facilitated, with iii. detected tunnel lining damages illustrated in clusters). Reproduced from (Stent et al., 2016)

Periodic tunnel inspection can produce a large amount of 2D images. Wang and Cheng (2020) proposed a pixel-level semantic segmentation of closed-circuit television (CCTV) images of underground pipes using a unified network, named DilaSeg-CRF that incorporates a deep CNN and the dense Conditional Random Field (CRF) method to improve segmentation accuracy. Figure 33 shows that the integration solution (DilaSeg-CRF) enhances segmentation performance in comparison with the fully convolution network (FCN-8s), dilated convolution (DilaSeg-Basic) and multiscale dilated convolution (DilaSeg). Zhao et al. (2020) proposed an image recognition algorithm for object detection, semantic segmentation and instance segmentation of leakage defects of metro shield tunnel by employing Mask R-CNN. Besides defect detection of tunnel lining, deep learning algorithms have been used on sewer pipe condition assessment (Hassan et al., 2019; Kumar et al., 2020).

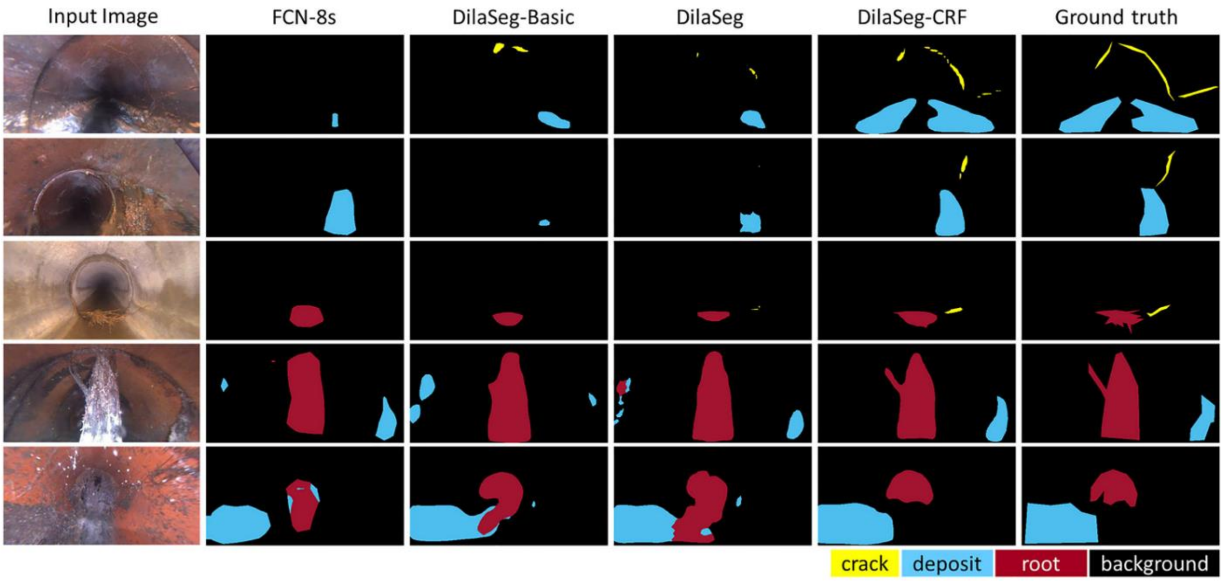


Figure 33 Comparison of segmentation results on multiple defects of closed-circuit television (CCTV) images from a sewer pipe inspection in the United States (FCN-8s: fully convolutional network, DilaSeg: a network with dilated convolution proposed by the authors, CRF: conditional random field). Reproduced from (Wang and Cheng, 2020).

Apart from interpretable data captured as 2D images. 3D data are less vulnerable to lighting conditions and having better information presentation with a reduced amount of noises. Examples of using 3D data can be found in pavement crack detection, such as in Zhang et al. (2017) that combined 3D laser imaging of pavement surface with a CNN architecture, named CrackNet. The architecture emphasised on pixel-perfect accuracy by removing the pooling layers and designing feature extractor specifically enhancing the contrast between crack and background, the proposed network outperformed traditional algorithms of machine learning and image processing. Fei et al. (2020) improved the original CrackNet by deepening the network structure with a reduced number of parameters for enhanced computational efficiency. However, these advances in 3D data interpretation leveraging deep learning are yet to be applied in damage and change detection of underground structures.

5. Discussion and perspectives

In this section, we examine the opportunities and challenges faced by adopting BIM, computer vision and their related technologies from four perspectives: 1) incorporating GIS and 3D geological modelling into the as-designed BIM workflow; 2) construction simulation and machine sensing techniques for modelling of the dynamic ground-machine-structure interaction; 3) computer vision-based infrastructure sensing and analysis that ensures the accuracy and reliability of the as-built BIM model; and 4) the capabilities of robotics and automation in collaboration with machine learning and computer vision techniques.

5.1 As-designed BIM, GIS and 3D geological modelling

At the design and construction stages, as-designed (can also be referred to as-planned) BIM models intend to enhance the efficient collaborations among participants from different disciplines. Geospatial information as an important stream of data should be used with other systems that collectively form a repository centring around infrastructure-related information. The couplings of lifecycle information management capacity provided by BIM and locational clarity offered by GIS showed prospective benefits. However, technical issues still remain in the consolidation processes. Apart from the dissimilarities between IFC and CityGML data structure, immaturity of infrastructure specific IFC data schema also hinders the establishment of an effective confederation of the two systems. Nevertheless, significant steps are taken towards formalising BIM application and its data exchange technologies by developing schema standardisation for infrastructure (roads, bridges, tunnels, etc.), which will become an integral part of IFC 5.0. The two domains can expect more accessible and reliable interaction for the planning of future infrastructure projects.

3D Geological modelling integrated with GIS in a spatial context is substantial for the construction of underground infrastructure. This imperative piece of information can be effectively incorporated into geotechnical modelling and analysis to provide design validation and stability assurance of the buried structures. The acquisition of the information, however, is only possible when the geological data is maintained in an accessible environment. Collaborative efforts from both government and industry are required in upholding the creation of open-data environments that will benefit future underground construction projects by improving the shareability of information. Examples of promoting data openness have been made for buried utility infrastructure, such as the Yarra Valley Water (YVW, an Australian water network operator) (YVW Australia, 2020) and Scottish Road Works Commissioner (SRWC) (SRWC Scotland, 2018b). YVW Australia (2020) provided full public access to its buried asset data via an interactive online map through a GIS system, and SRWC Scotland (2018b) is developing a dataset named the Scottish Community Apparatus Data Vault that will link with the Scottish Road Works Register (SRWC Scotland, 2018a) for access to information on the location of underground pipes and cables.

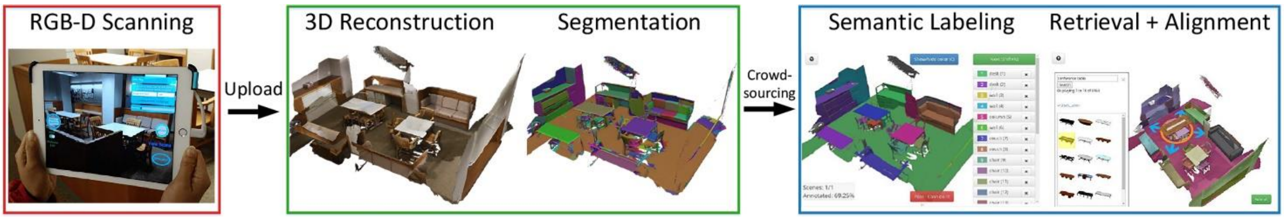
5.2 As-built BIM and image-based 3D computer vision

BIM models can be used for as-designed visualisation with accurate 3D geometrical and semantic information of underground structures, but still lack the capabilities to recognise construction state, predict engineers/machines activities, and manage the construction schedule. With the increased availability of 3D sensing technologies (e.g., RGB-D and multi-view cameras, and laser scanners) and machine learning algorithms, great efforts have been made in the fields of collaborative 4D BIM simulation in surface construction (Braun and Borrmann, 2019; Khosrowpour et al., 2014; Kropp et al., 2018; Turkan et al., 2012). Although machine learning and computer vision algorithms have been successfully implemented at different stages of underground construction, an increasing volume of data requires the design of sophisticated feature extractors, and powerful computational capabilities to improve the accuracy and performance for real-time applications.

Underground space (indoor) modelling/monitoring and VR/AR systems are on the rising need for incorporating depth into semantic segmentation of the objects. Garcia-Garcia et al. (2017) conducted a comprehensive review on deep learning techniques for image semantic segmentation, the popular large-scale segmentation datasets, including the number of classes, training splits, and data format (2D/2.5D/3D) are summarised. 2D dataset and its applications in underground construction are presented in Sections 2.2.2 and 4.2.2. RGB-D or 2.5D dataset and pure volumetric or 3D datasets and reconstructed scene meshes are being of great interest for computer vision and machine learning researchers in the field of indoor environments. The proper selection of 3D sensing technology is an essential step to ensure accurate monitoring. The advantages of multi-view or RGB-D cameras are as a low-cost alternative for quantitative monitoring (Franco et al., 2019), which can be robustly incorporated with robotic systems such as drones to perform monitoring tasks (Freimuth and König, 2019; Kalaitzakis et al., 2019). RGB-D cameras have been increasingly employed in real-time surface mapping and reconstruction of the complex and arbitrary indoor environment for their affordability (Avetisyan et al., 2019; Dai et al., 2017b; Newcombe et al., 2011). An example is illustrated in Figure 34a (Dai et al., 2017a), where the RGB-depth data was captured and processed through surface reconstruction and instance-level semantic labelling. The benchmark tasks using the established 3D dataset and deep learning-based 3D scene understanding included 3D object classification, 3D object retrieval and semantic voxel labelling. In addition, stereoscopic 3D-360 video systems have been developed for capturing and rendering 3D 360 videos and images that are suitable for viewing in virtual/augmented reality (VR/AR), such as Facebook's open-source Surround 360 (Facebook, 2016). The most well-known 2.5D/3D indoor databases include NYUDv2 (Silberman et al., 2012), SUN3D (Xiao et al., 2013), SceneNN (Hua et al., 2016), Stanford 2D-3D-S (Armeni et al., 2017), ScanNet (Dai et al., 2017a) and Matterport3d (Chang et al., 2017). Interested readers are referred to (Naseer et al., 2018) for a detailed comparison among various 2.5/3D datasets.

3D computer vision offers a more quantitative method to understand the condition of underground infrastructure. For example, structural deformation and vibration can be measured by implementing 3D digital image correlation (3D-DIC) in combination with object tracking and image registration techniques (Franco et al., 2019). Other 3D representations such as point clouds and voxels produced by image-derived methods, RGB-D cameras, LiDAR and SAR systems have also attracted attention from computer vision and machine learning communities (Xie et al., 2020). Figure 34b demonstrates a framework named SegCloud for voxel-based semantic segmentation that combines 3D FCN with trilinear interpolation and fully connected conditional random fields (Tchapmi et al., 2017).

These hot topics in deep learning and computer vision demonstrate great potentials for escalating the degree of automation in any construction environment. Meanwhile, through actively engaging robotic systems, they present even greater values for underground construction that often take on activities in compromised conditions. In addition, this automation in data acquisition, analysis and application facilitates the provision of maintenance scheme and resources coordination. Among the applications, 3D scene acquisition, object detection, segmentation and 3D model alignment (can easily be replaced by instance-level BIM models at higher LoDs) could be effectively applied to the simulation models (VR/AR) of underground infrastructure.



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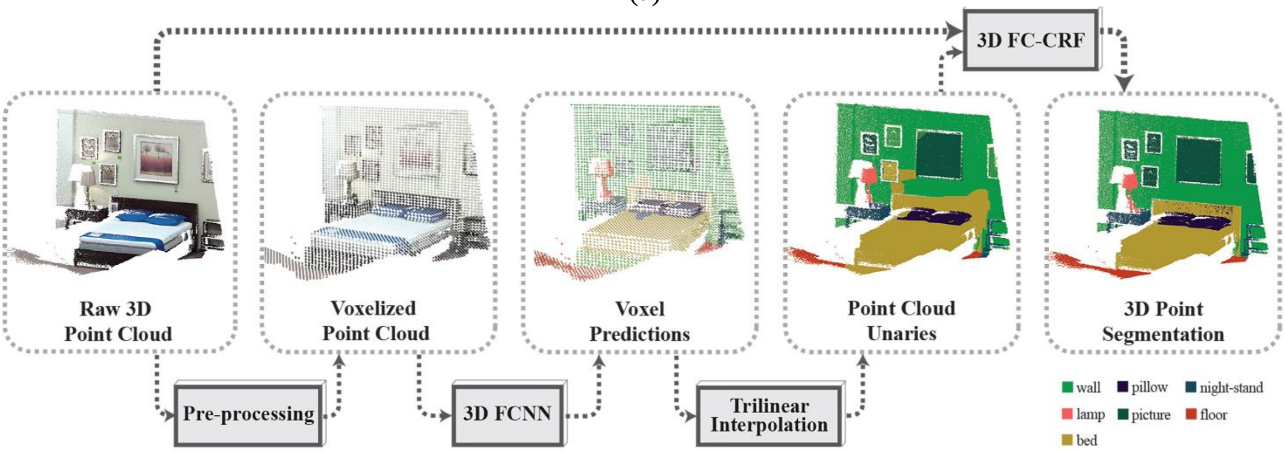


(b)

Figure 34 3D image and point segmentation: (a) overview of a framework constituted of RGB-D scanning to 3D surface reconstruction and segmentation to instance-level semantic labelling and CAD model alignment. Reproduced from (Dai et al., 2017a), and (b) a framework for voxel-based semantic segmentation named SegCloud, where raw point clouds are voxelised and processed by 3D FCNN (fully CNN) in combination with trilinear interpolation and 3D FC-CRF (3D fully connected conditional random fields). Reproduced from (Tchapmi et al., 2017)

5.3 Integration of BIM and modelling/monitoring

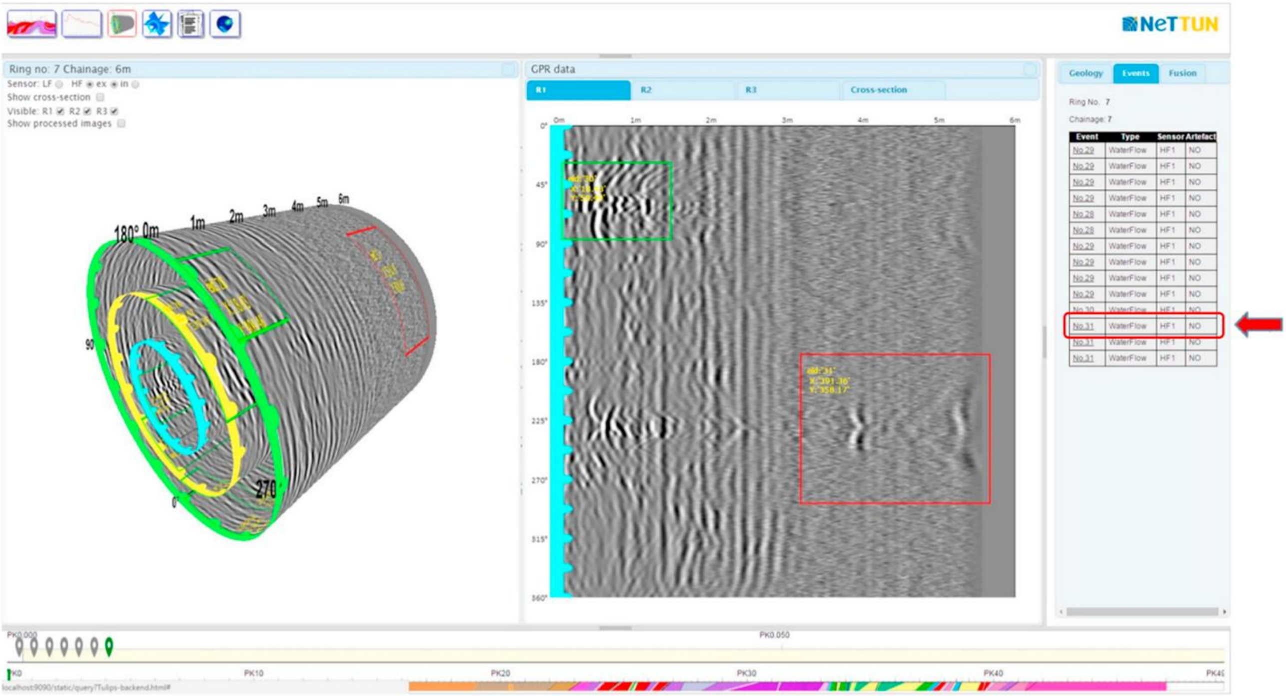
Simulation and modelling are another central technology to support Industry 4.0, which can be applied to improve the design of underground infrastructure and enhance the safety of humans, machines, excavated ground and existing buildings. With reference to the simulation of ground-machine-structure interactions involving numerical calculations, some existing research on the unified information and numerical modelling has been discussed in Section 3.4. BIM for underground structures examines a range of factors different from that for surface buildings (e.g., geological, geotechnical and geographical). The popular BIM modelling/simulation tools on-market are falling short of interfacing with specific underground applications (e.g., numerical modelling for geotechnical problems). This urges the development of IFC standards and coordination tools based on understanding the BIM workflow within underground construction; otherwise, extensive customisation would be required (e.g. plug-ins, middleware, code-based execution environment), which can be costly and time-consuming.

Simulation regarded as a visualisation tool facilitates early identification of physical constraints and uncertainties to allow the timely implementation of mitigation measures. The BIM-based simulation also offers enormous opportunities for construction monitoring by helping identify and quantify any mismatches (e.g. misalignments, deviations from schedules) between the as-designed (or the simulated, i.e. projected development) and the as-built models (i.e. completed construction). Centralised information management can be enhanced by incorporating real-time data and interpreted information into the federated BIM model. However, with different data acquisition and processing methods, the data features and applications take diverse forms. Therefore, the integration will be determined upon project specifics. For example, in a task of applying a CNN-based instance segmentation algorithm to detect damages such as leakage, cracks and spalling on tunnel linings, photos obtained from the inspection can each be assigned a unique identification (ID) number associated with the ID/location along the tunnel where the photo has been taken. Therefore, the information regarding the damage (e.g. whether damage occurs, if yes, damage type and severity) can be updated to the BIM model for further actions, such as scheduling maintenance. This example demonstrates a possible use case of the BIM process that largely leverages computer vision-based techniques and the 4D concept. In addition, BIM models enriched with geometric and semantic information can effectively be used to constitute datasets for VR/AR-based 4D simulation of underground construction, serving as valuable training resources.

5.4 Automation and robotics

An emerging trend intended to sustain a safe subsurface excavation and operation environment is to introduce robots on top of traditional ahead-prospecting, machine and structural monitoring gadgets. A key aspect of achieving digital twin is fully automated data acquisition and processing (Uhlemann et al., 2017), which inevitably requires the use of robotic systems. The research efforts have mainly been two-fold. One is an automated data acquisition and processing engaging robotic systems. The other has been navigation in a dark environment and mapping the underground areas without necessarily demanding GPS and ambient light. Both views are serving the purpose of assisting human engineers in construction and maintenance related tasks that are challenging and potentially dangerous in an underground environment. With many examples explored in Section 4 actually employed autonomous systems, there have also been efforts emphasising robotics techniques for tunnel inspection, such as (Cipolla, 2015; Loupos et al., 2018; Menendez et al., 2018), as well as investigations into improving the underlying algorithms and data fusion robustness to support the physical-world applications, some examples can be found in (Imani et al., 2018; Lech et al., 2016; Zeng et al., 2019).

TBM can be regarded as a semi-autonomous robotic system excavating ground constituted of varied geological conditions, which are anticipated through a series of surveying and geophysical prospecting techniques. Meanwhile, modules constitute a TBM such as the cutterhead is often a sensor-embedded unit that collects data for potential real-time interpretation. Autonomously operating tunnelling systems that aim to remove machine operators from the dangerous underground environment have been realised. One of such solutions is the autonomous pilot system designed for TBM navigation that is capable of on-board map generation and path planning (Ferrein et al., 2012). Other solutions include the BADGER (RoBot for Autonomous unDerGround trenchless opERations, mapping and navigation) that incorporates robotics control techniques, sensor fusion and machine learning (BADGER Consortium, 2017), TBM-cutter changing robot (Yuan et al., 2019), and CPS-enabled autonomous supporting pressure balance control for TBMs (Zhang et al., 2020b). Moreover, web-based application platform, as illustrated in Figure 35, has been developed for providing visualisation and automatic feature detection based on real-time TBM parameters, sensing data (e.g. GPR and seismic data) and geological map for collaborative interpretation and decision-making (Wei et al., 2019). The real-time insights into the ahead geology are favourable in underground excavation; however, the algorithms or models used in these scenarios may not necessarily generalise well to unseen data if they are deduced based on certain ground types. Adaptive selection of machine learning models is thus essential.



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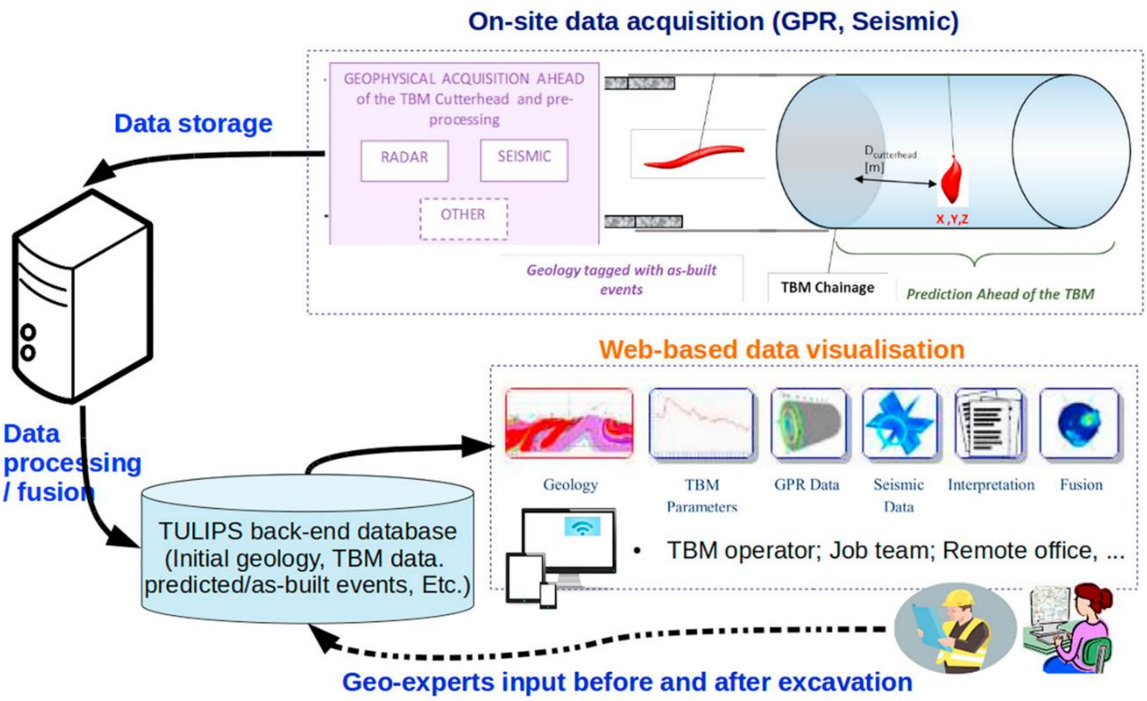

(b)

Figure 35 (a) An example of visualising GPR data in cylindrical and planar view as a function provided by the (b) visualisation platform, forming part of the workflow connecting management and analysis of imaging and contextual data for tunnel ground. Reproduced from (Wei et al., 2019).

Aerials and legged robots have been developed to carry out autonomous exploration and mapping in underground areas. For details of robotics, refer to Springer Handbook of Robotics (Siciliano and Khatib, 2016). A review on the research advances and findings of employing ground robotics in tunnel-like environments, focusing on topics of localisation, navigation, and communications can be found in (Tardioli et al., 2019). Most recently, the 3-year (2018-2020) Subterranean (SubT) Challenge launched by DARPA (Defense Advanced Research Projects Agency) inspiring robotic solutions for underground mapping and rescue. The results have demonstrated the capability of robotic systems, in collaboration with computer vision techniques, for autonomous navigation and extensible subsurface applications such as structural inspection and abnormality detection particularly in GPS-denied environments (DARPA, 2020). Team Explorer (Explorer, 2020) and team CoSTAR (CIT, 2019) of the Systems track are the winners for the Tunnel Circuit and Urban Circuit, respectively. Example of a mapping and navigating system that realises commercialisation is the Hovermap for drones based on LiDAR (Jones et al., 2020). The scanning unit has claimed for the completion of the first autonomous beyond-visual-line-of-sight flight in an underground mine in 2018 and has been paired with legged robots in the SubT Challenge (CSIRO, 2020).

5.5 Summary and an interactive platform

Ripe with enhanced data storage and transmission capability, extensive sensor deployment forms the IoT of underground infrastructure to enable real-time information feedback regarding the location and condition of both personnel and equipment to provide better control over the underground environmental safety. This requires extensions of IFC-based object definitions correspondingly to accommodate the information. Meanwhile, the data generated at a rapid rate demands faster processing and analysis, and thus is highly reliant of robust hardware and software. Tesla's driverless cars is an example of such a need (Talpes et al., 2020). Within underground infrastructure network, this trend can also be envisioned by having pilot projects initiated to implement high-speed image capturing and processing devices on operating trains to assess tunnel-lining conditions (Hayakawa et al., 2018).

BIM within underground infrastructure shares similarities with that for surface building in the majority of the technical perspectives, such as procedures engaged in the graphical model establishment, data schema for maintaining interoperability, as well as safety assurance (e.g., natural and human-induced disasters: earthquake and fire) of as-built model underpinned by infrastructure sensing (Lu et al., 2020). However, the underground construction faces unique challenges in visually interpreting the ground-machine-structure interaction through an opaque medium featured with huge uncertainties. To mitigate these challenges, an interactive platform (Figure 36) is taking the Metro Tunnel Project in Melbourne as an example, depicting the comprehensive, integrated solutions discussed above. It consists of four modules with interaction supported by data exchange protocols. By drawing on knowledge from project-specific ground investigations and existing GIS data, geological and geotechnical quantifications are realised to provide a foundation for BIM-based structural design, with its feasibility verified by numerical simulation. During construction and operation, autonomous or semi-autonomous devices are engaged to acquire data that reflects the ground-machine-structure interactions and structural integrity. The BIM model is then reconciled with as-built data for improved accuracy and reliability. Within this interactive platform, we regard the BIM environment as a digital repository, a modeller and a visualisation tool to correctly reflect the status of the infrastructure throughout its lifecycle.

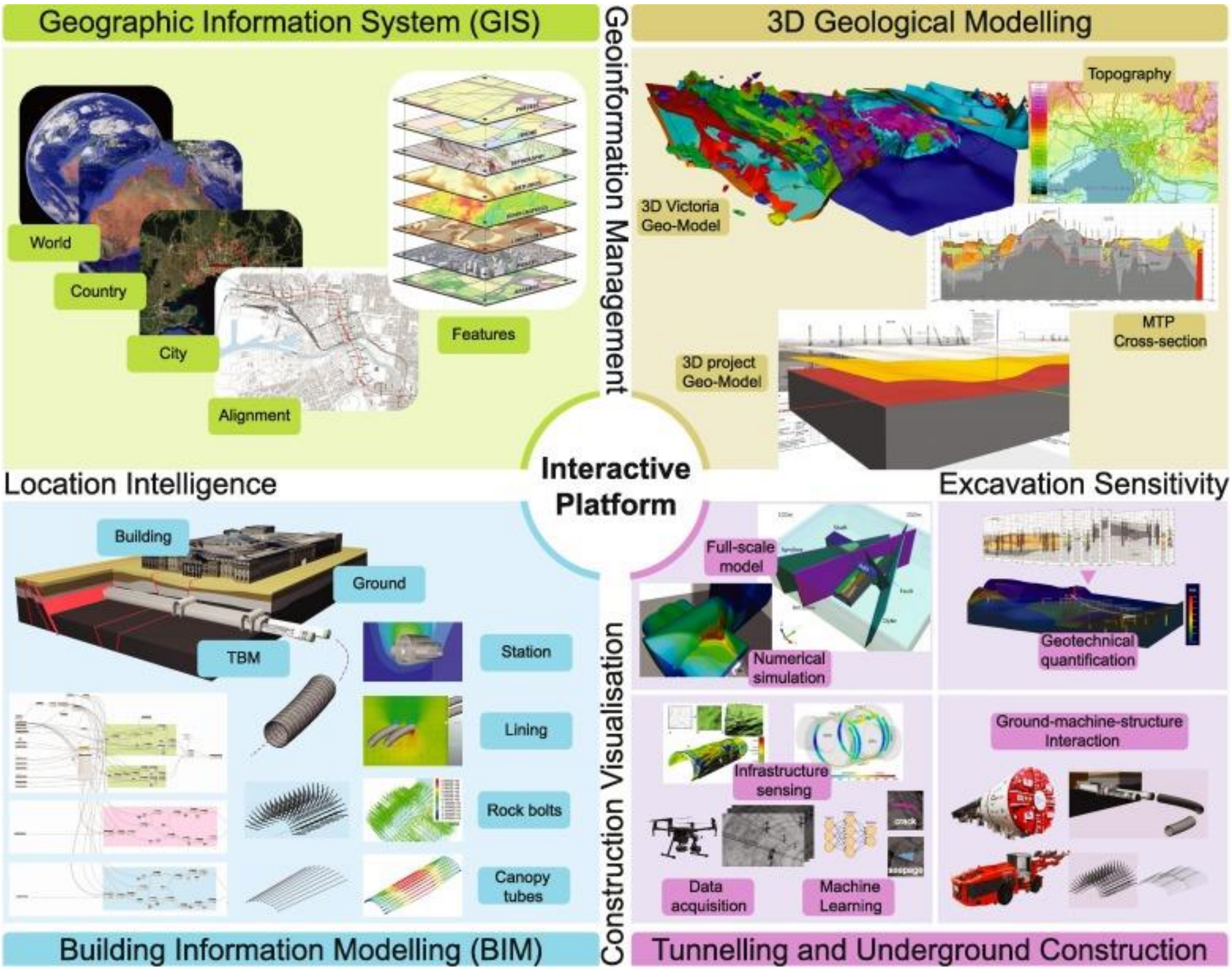

Figure 36 Interactive workflow of GIS, 3D geological modelling, underground construction and BIM for underground infrastructure.

6. Conclusions

With a digital transformation agenda expanding into the domain of underground, we examined the state-of-the-art applications, limitations and future opportunities of BIM, machine learning and computer vision-based techniques that are believed to demonstrate huge potential in the digitisation of tunnelling and underground construction.

BIM enables the information collection, exchange and linking throughout a project's lifecycle. The visualisation and interoperability facilitated by BIM processes are especially important to underground construction that engages interdisciplinary participation and multi-environment interaction. The geological uncertainties and localisation difficulties of already laid infrastructure are challenges not seen in building construction. Underground BIM thus requires consideration of geographical and geological features, and harnessing data exchange solutions to establish comprehensive and integrated information resource.

As key AI technologies, machine learning and computer vision are consolidating into a powerful tool for big data analysis. Machine learning algorithms, with profound history in helping computers to learn from data by automatically extract patterns, have established wide applications in data interpretation of the underground environment and machine performance. Meanwhile, advances in both optical and non-optical devices coupled with accessible robotic systems have produced a large volume of images or image-like data that have effectively boosted the development of deep learning and stimulated recent advances in computer vision. The evolution in data analytics in conjunction with the increase of sensing deployment helps capture the situational variations during system interaction and operation monitoring. In combination, they offer to provide reconciled BIM model updated with as-built data, and thus supporting engineers to make informed decisions.

We also introduced an interactive platform by taking the Metro Tunnel Project in Melbourne as an example. This platform considered the comprehensive and collaborative integration of GIS, 3D geological modelling, construction methods, and sensing technologies into BIM in order to form a reliable basis for decisions and management during the lifecycle of an underground project. Finally, challenges and opportunities were identified to assist the set-up of the future research plan.

Acknowledgements

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