A Review of Present Status & Future Aspects of Computer Vision and Machine Learning Techniques used in Underground Tunnel Engineering: Digital Revolution

Sumit Kumari[1], Vikas Siwach[2], Yudhvir Singh[3]

{sumitmalik97@gmail.com[1], singhvikashuiet@gmail.com[2], yudhvirsingh@rediffmail.com[3]}

CSE Department, UIET MDU, Rohtak, Haryana, India[1, 2, 3]

Abstract. The AEC (Architecture Engineering Construction) industry is going through the phase of a digital revolution driven by bombarding it with digitization and automation. These developments can be possible due to the advancement in research areas of information technologies and computer science which attracted many researchers. Simultaneously, in the population-driven underground work, the technological involvement has also been increased with the help of the digital revolution. Underground tunnels are important assets that constantly demand effective construction, planning, and maintenance, etc. Therefore, applications of computer vision and machine learning techniques in underground tunnel engineering provide different sets of challenges and opportunities by enabling larger clarity and accuracy into the subsystems and process of underground tunnel engineering. The main aim of this study is to examine the current state of computer vision and machine learning, as well as related approaches that aid in the digital growth of underground tunnel engineering. In this paper, the research of the last two decades in the area of underground tunneling by using computer vision and machine learning has been discussed and compared. In addition, this research will help the researchers to explore the digital revolution of underground tunnel engineering.

Keywords: Artificial Neural Networks, Computer Vision, Digital Revolution, Machine Learning, Deep Learning, Underground Mining.

1 Introduction

It's been 20 years since this new era of digitization and automation has been started in the 21st century and many researchers believed that the AEC industry is having some huge transformation. This transformation will only be achieved when the joint use of technologies meets the demands of establishing interconnected, controlled, and indigenous processes, products, and systems. In the AEC industry, underground tunneling is the main reason for rapid urbanization as it attracted many research communities. Underground tunneling is not the only one that is affected by the digitization wave, but also every infrastructure-related process is being affected by this. There are several examples available where mega-scale projects used advanced data storage solutions and computing methods such as London Crossrail in the UK [1], the Badaling station of Beijing-Zhangjiakou in China, and the MRT Line 2(SSP) in

ICIDSSD 2022, March 24-25, New Delhi, India

DOI 10.4108/eai.24-3-2022.2318770

Malaysia [2], etc. While considering several opportunities, digitization in urban-underground-development is confronted with some obstacles, which are created by: 1) Geological uncertainty, 2) The inherent complexity of spatial opacity, 3) Ground-machine-structure interactions, and 4) Working in a high-risk environment.

The digital revolution efforts within the underground tunneling towards a digital solution revolve around two reasons:

- *Need*: The rapid urbanization escorted by the growing populations inspires the utilization of underground space for tunneling [3]. For example, the population of Beijing is estimated at over 21 million people. These 21 million peoples cover a distance of 16140 square kilometers. To serve its people, Beijing has developed an extensive metro system that covers an area of 637 square kilometers with 22 metro lines and 391 stations[4].
- *Ease*: The burden of maintenance of previous projects is greatly influenced by the lack of digitization that visualizes and updates information. For example, London has the earliest metro systems network escorted with the wide utility of networks crossing with each other. These crossing results in accidental strikes on underground cables and pipes which cost a loss of around 1.2 billion British pounds yearly [5]. To address this problem, the UK government's geospatial commission is working on an underground resource registry, which will give digital maps of subsurface cables and pipes for proper data access, use, and sharing [5]. Similarly, the Singapore-ETH center is working with Singapore's land authority to create a digital twin of the city's undergrounds using 3D technology [6], following the country's national plan, which prioritizes the efficient use of underground space.

These reasons have identified the need for using digital technologies to boost the effective and efficient development- planning, and management of underground tunneling.

Computer vision and machine learning approaches are seen as important aspects in the scenario of industry 4.0 for underground tunneling construction, as they have demonstrated convincing results in the digital transformation process [7]. These technologies have demonstrated the combined powers of data collecting, management, and processing, therefore reliance on smart technology continues to grow. The generated data is associated with three types of Vs i.e. Volume, Variety, and Velocity that has crossed the capability shown by the traditional methods. Therefore, computer vision and machine learning approaches demonstrate a great capability for big data analysis. Several applications have been proposed based on computer vision and machine learning approaches that show the digitized state of underground construction [8].

In this paper, we present the computer vision and machine learning techniques based on two important stages of underground tunneling that is:

- At the construction stage
- The Operation and Maintenance stage.

The construction stage is again divided into three subparts: 1) Geological prospecting, 2) Tunneling Boring Machine performance, and 3) Ground prediction and evaluation. Similarly, the operation and maintenance stage is divided into two subparts: 1) Change detection based on point set, and 2) Damage and change detection using images.

This paper is organized as, in the next section introduction about machine learning and computer vision has been given. In section 3, the application of these techniques specific to underground tunneling has been demonstrated. The conclusion is given in section 4 which has been focused on the paper outcome and future perspective of this research.

2 A Gentle Introduction to Computer Vision and Machine learning

Big data and its jointly related field such as computer vision and machine learning have received huge attention in the past decade. This attention has benefited the wide range of applications in the context of underground tunneling including design, construction, and maintenance.

2.1. Computer Vision

Computer vision is defined as a process of extracting useful information by analyzing images or videos, to understand the underlying physical world. It has been adopted in many ranges of applications such as face detection, person tracking, stereo matching, etc.[9]. Even though deep learning outperforms several techniques mainly related to object detection and recognition. But still, computer vision techniques are better than the traditional methods in the context of 3D reconstruction and panoramic vision [10]. Computer vision systems are essential for recording and capturing the constantly changing condition of construction and, as a result, assisting in decision-making. According to some researchers, the intelligence of the built environment may be leveraged to establish awareness and create values when autonomous/semi-autonomous platforms are employed for data collecting and integrated with machine learning approaches.

2.2. Machine Learning

It is believed that machine learning has a very profound history. In 1952, Arthur Samuel introduced the game-playing program by using the concept of machine learning. In 1959, machine learning was defined as a "*field of study that gives computers the ability to learn without being explicitly programmed*" [11]. Generally, these algorithms are designed to learn from data by automatically extracting patterns. "*Learning*" plays an important role in machine learning algorithms. Therefore, Mitchell [12] defined learning as a "*computer program is said to learn from experience E concerning some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E*". Several tasks, according to some researchers, can be simply addressed given prior learning and performance experience. Consider the case of a tunnel engineer who wishes to identify a crack in a tunnel portion. The goal is to find a label that says "crack" or "no crack" on any image taken within the tunnel. The performance measure for this crack detector maybe its accuracy, and the training experience could be a collection of photos with labeled images of cracks or no cracks. Machine learning is typically classified into three categories: supervised learning, unsupervised learning, and reinforcement learning. The problem of crack detection that has been discussed is an example of supervised learning. The papers included for this review are primarily based on this sort of learning, which is supervised learning. Robotics, autonomous vehicle control, neuroscience research, and voice and natural language processing are all examples of tasks where machine learning algorithms are valuable.

3 Computer Vision and Machine Learning Techniques used in Underground Tunnelling

Several technologies, including computer vision and machine learning approaches, have been employed in subterranean tunnel construction for various applications such as structural and stability health monitoring, geological anomaly predictions, and as-built quality control, and among others. In this review, strategies implemented in the underground tunnel construction mainly related to underground inspection and maintenance have been discussed [13]. Geophysical prospecting and sensing deployment, generally, produced a huge amount of data during tunneling and post-construction maintenance. Therefore, several researchers have applied machine learning techniques to the data produced from geo-prospecting [14]. Similarly, computer vision techniques is also been applied to infrastructure inspection and monitoring [15]. This section provides reviews and examples of the computer vision and machine learning techniques that are widely applied at the construction stage, operation, and maintenance stage as shown in figure 1.

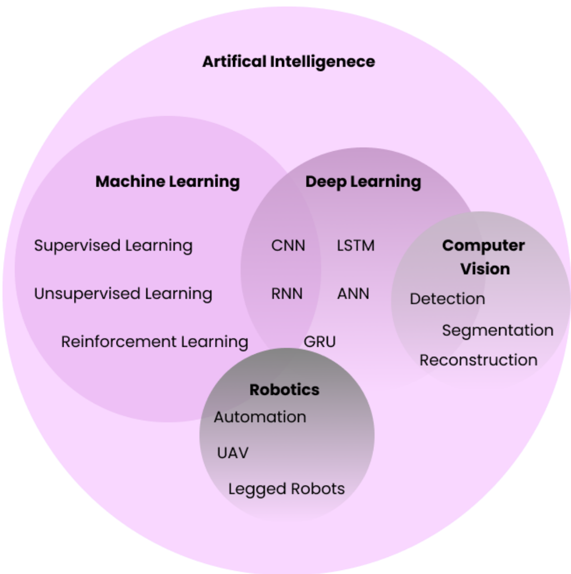

Fig. 1. AI-related fields that can be used in underground tunneling

3.1 The Construction Stage

During the construction stage, a huge amount of data has been generated, that can be widely divided into three parts as waveform-based geological prospecting, machine performance, and ground prediction and evaluation. The computer vision and machine learning techniques for waveform-based geological prospecting can be demonstrated as:

3.1.1 Geological prospecting

Several geophysical methodologies is been applied to underground tunnelling to gain information on local geophysical conditions. A detailed review of geophysical methodologies is been proposed by Li et al. [16] where the technological and applications principle of geophysical methods have been deliberated. Wu and Lin [17] proposed a model called InversionNet that figures out how to transfer seismic waves to an underground velocity model, as the full-wave inversions play an important role in the subsurface characterization. Generally, seismic wave-based approaches are used for detecting geophysical discontinuity [18]. Seismic waves are created by hammer vibrations and explosions, which are detected by sensors placed on the surfaces. This approach identifies various types of rocks based on how long it takes for waves to be reflected due to lithological discontinuities. In some cases, during the process of constructing the underground water supply tunnel, the ANN (Artificial Neural Networks) is used to anticipate the worst geological zones by maintaining the relationship with TSP-203 (Tunnel Seismic Prediction)[19]; which results in knowing the seismic properties [14]. Further, the fully simplified CNN (Convolutional Neural Network) has been used from the U-Net [20] by proposing to train 3D datasets of seismic images. This method helps in localization and context capturing, as it contains the symmetrical expanding path and contracting path respectively.

Microseismic functions mainly predict hazardous rockburst and assess rock mass stability. Rocks generate low-level seismic signals when they are tensed [21]. Therefore, deploying the microseismic monitoring systems underground can interpret those low-level signals and allow us to locate the seismic source. These resulting signals can help in improving excavation safely and can be used to train NN (Neural Network) for feature extraction and pattern recognition [22]. In this study, the authors have developed a model called the PhaseNet by using the DNN (Deep Neural Network) algorithm to predict the three components of the waveform. Usually, before doing any excavation process, the detection of utility networks and knowledge of underground infrastructure is required for adequate management and planning for underground space. This is important because some countries have limited terrestrial areas such as UK and Singapore. Therefore, they have launched several programs to digitalize underground space by mapping and assessing the underground construction [6], [23]. Both these studies, record data on the field by using geophysical techniques like GPR (Ground Penetrating Radar). GPR depends on electromagnetic waves that detect discontinuity and alien-like substances by identifying signal attenuation from the targeted objects. A study developed a pattern recognition system that involves pre-processing to minimize the noise, feature extractor, and SVM (Support Vector Machine) classifier. This study helps in detecting and classifying buried objects from GPR imaging. GPR is also used in geological drilling in an underground tunnel along with being employed for an already laid utility network. The variation in waves of geological heterogeneity such as fractured rocks and groundwater can be characterized and detected by GPR when the images are reviewed by the analyst. However, images evaluation highly depends on the analyst's experience [24]. The database that contains the GPR images plays an important role in the management system to enable the decision-making process and collaborative interpretation based on functional visualization. In this work, the data has been captured using the GPR and a backend database has been created. To obtain geological insights, seismic methods have been used. With the help of these databases, DNN can be used to learn patterns and extract features. Liu et al. [25] used the DNN architecture for mapping permittivity maps to GPR data. This method can be used to reconstruct tunnel lining defects.

3.1.2 Tunnelling Boring Machine Performance

Machine learning techniques have been widely used on operational data, specifically in tunnelling boring machine operations. It mainly fulfils the prediction of geological conditions and forecasts TBM performance. For example, Benardos and Kaliampakos proposed the ANN to predict the TBM advance rate. With the help of ANN, the authors determine the effect of parameters on TBM performance. Further, the SVM algorithm is used to develop a prediction model for TBM penetration rate. In addition to these, The GIS (Geographic Information System) platform has been used to improve the visualization capability and helps in the decision-making process for routine tunnel maintenance. Just like supervised machine learning approaches, few studies have also used unsupervised machine learning techniques for analysing operational data during underground tunnel construction. For example, Zhou et al. [26] suggested integrating complex network theory, and spectral clustering, for shield tunnelling by using multidimensional datasets. The results of this were used to analyse the shield machine's cutter maintenance and to infer geological condition adaptability. In another example, Gao et al. [27] predict the operating parameters in real-time by using RNNs (Recurrent Neural Networks)

3.1.3 Ground prediction and evaluation

Underground tunnel construction sometimes induced ground deformations. Therefore, the machine learning approaches have been selected to evaluate the geological conditions in tunnels [28] and to predict the tunnel settlement induced by TBM tunneling. These approaches are better than the terrestrial measurement techniques as they are time and material-consuming. Simultaneously, increasing power in remote sensing technologies such as InSAR, which helps in providing accuracy in near-real-time. Classical examples of applying InSAR include landslide deformation, assessment and monitoring of ground scheduling, and building damages induced by tunneling [29]. However, several attempts have been made on enhancing the existing approaches and limits to process the huge amount of images. But still, accuracy depends on human interpretation and expert knowledge. For example, Anantrasirichai et al. [30] developed a CNN-based framework for detecting ground deformation in the London-Northern line extension with the help of UK velocity maps and high-resolution InSAR images. Machine learning approaches are also used in predicting geological conditions with the help of TBM operating parameters. Zhang et al. [31] predict the geological conditions i.e. changing rock mass type by using an SVM classifier. The authors claim that their proposed method provides an average precision of 98.6% after compressing big TBM operational data with the help of unsupervised learning. In another study, the authors combine the approaches i.e. ANN and Simulated Annealing to predict the distance between the two planes, the orientation of discontinuities, and rock mass parameters based on TBM driving parameters.

3.2. Operation and Maintenance stage

The advancement in optical sensors and computer vision techniques attracts researchers to use and apply to the general inspection and monitoring of underground tunnel infrastructure[32]. In the traditional approach, inspecting these tasks involves computer vision-based data processing and data acquisition that helps in detecting any change on the surface as well as any damage. Whereas, monitoring can be done by using load cells, extensometers, and strain gauges that helps in understanding the structural integrity. However, the results attained require dense sensor employment as they have a low spatial resolution. Therefore, a vision-based, non-contact monitoring framework with the help of photogrammetric approaches has been preferred as they have high spatial resolution and allow flexibility in maintenance. In the next subsection, examples of computer vision and machine learning approaches that monitor and inspect the underground tunnel construction are discussed.

3.2.1 Change detection based on point set

Mobile and terrestrial laser scanning is increasingly applied in water leakage, tunnel deformation, and the detection of structural discontinuities. An automatic rotation up to 360º can be used to achieve a dataset that covers the full surface. Researchers provide geotechnical insights by usually converting point cloud to visual representation. Yi et al. [33] used the LiDAR point cloud recorded with the help of TLS to develop a system to model the underground tunnel infrastructures.

3.2.2 Damage and change detection using images

For general monitoring and inspection of underground tunnel infrastructure, computer vision techniques have been deployed. These techniques help in detecting structural deterioration such as seepage and spalling or cracks with the help of image datasets that are acquired during the inspection [34]. Several robotics systems and inspection vehicle is engaged in tunnel lining defects that are equipped with a camera to acquire 2D and 3D profile of the surfaces. For example, in a review on underground tunnel infrastructure maintenance in Japan by [35], a vehicle named MIMM-R had been established. It had been claimed that it's a high-speed mobile inspecting vehicle that is assembled with the camera, electromagnetic wave radar device, and laser scanner.

Traditionally, computer vision and machine learning technologies have been used to identify any damage or change in the tunnel in low-to-intermediate image processing methods. In recent times, several efforts have been made with the help of photogrammetric methods that includes SfM (Structure from Motion). It helps in creating 3D reconstruction with the help of 2D images that depend on the extraction of invariant characteristics from overlapping images [36].

Usually, tunnel monitoring can generate a huge amount of 2D images that benefited the R&D process. Wang and Cheng [37] combined Deep CNN with Deep CRF (Conditional Random Field) to create the Dila-Seg-CRF unified network, which can be utilized to produce pixel-level semantic segmentation of CCTV (Closed-Circuit Television) images of subterranean pipelines. Zhao et al. [38] used the Mask R-CNN and developed an image recognition algorithm. This algorithm helps in semantic segmentation, object detection, and instance segmentation of leakage defects. Similar to 2D picture data, 3D image data has been used in numerous research projects because it reduces noise and is less susceptible to lighting conditions.

4 Conclusion

This paper discussed the digital transformation in the domain of underground tunnel engineering. In this paper, the current studies related to computer vision and machine learning approaches have been examined. These methods have a lot of potential for digitizing underground tunnels. Computer vision and machine learning are two key AI technologies that can be used to perform massive data analysis. Machine learning approaches have a long history in enhancing the performance of the machines for underground development by learning from the data by automatically extracting patterns. A huge volume of image-like data or images has been produced with accessible robotics systems that have integrated optical and non-optical devices. The advancement in optical and non-optical devices has effectively boosted the development of computer vision techniques in underground tunneling. In addition to these, the growth of data analytic also helps in the process.

References

[1] Huang, M. Q., J. Ninić, and Q. B. Zhang. "BIM, machine learning and computer vision techniques in underground construction: Current status and future perspectives." *Tunneling and Underground Space Technology* 108 (2021): 103677.

[2] “Catalyst for Change: BIM Implementation in the MRT Line 2 (SSP) Underground Works – BIM Portal.” https://bim.mymrt.com.my/catalyst-for-change/ (accessed Oct. 03, 2021).

[3] National Research Council. *Underground engineering for sustainable urban development*. National Academies Press, 2013.

[4] Wang, Ying. "Analysis and Evaluation of High-Quality Development Status of Beijing Transportation." *IOP Conference Series: Materials Science and Engineering*. Vol. 688. No. 2. IOP Publishing, 2019.

[5] Map of underground pipes and cables designed to save lives and prevent major disruption - GOV.UK.” https://www.gov.uk/government/news/map-of-underground-pipes-and-cables-designed-to-save-lives-and-prevent-major-disruption (accessed Oct. 03, 2021).

[6] Schrotter, Gerhard. (2020). Towards a Reliable Map of Subsurface Utilities in Singapore Digital Underground.

[7] Oesterreich, Thuy Duong, and Frank Teuteberg. "Understanding the implications of digitization and automation in the context of Industry 4.0: A triangulation approach and elements of a research agenda for the construction industry." *Computers in industry* 83 (2016): 121-139.

[8] Darko, Amos, et al. "Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities." *Automation in Construction* 112 (2020): 103081.

[9] Szeliski, Richard. *Computer vision: algorithms and applications*. Springer Science & Business Media, 2010.

[10] O’Mahony, Niall, et al. "Deep learning vs. traditional computer vision." *Science and Information Conference*. Springer, Cham, 2019.

[11] Samuel, Arthur L. "Some studies in machine learning using the game of checkers." *IBM Journal of research and development* 3.3 (1959): 210-229

[12] Jordan, Michael I., and Tom M. Mitchell. "Machine learning: Trends, perspectives, and prospects." *Science* 349.6245 (2015): 255-260.

[13] Bergeson, William, and Steve L. Ernst. *Tunnel operations, maintenance, inspection, and evaluation (TOMIE) manual*. No. FHWA-HIF-15-005. The United States. Federal Highway Administration, 2015.

[14] Alimoradi, Andisheh, et al. "Prediction of geological hazardous zones in front of a tunnel face using TSP-203 and artificial neural networks." *Tunnelling and underground space technology* 23.6 (2008): 711-717.

[15] Bao, Yuequan, et al. "Computer vision and deep learning–based data anomaly detection method for structural health monitoring." *Structural Health Monitoring* 18.2 (2019): 401-421.

[16] Li, Shucai, et al. "An overview of ahead geological prospecting in tunneling." *Tunnelling and Underground Space Technology* 63 (2017): 69-94.

[17] Wu, Yue, and Youzuo Lin. "InversionNet: A real-time and accurate full waveform inversion with CNNs and continuous CRFs." *arXiv preprint arXiv:1811.07875* (2018).

[18] Wu, Xinming, et al. "FaultSeg3D: Using synthetic data sets to train an end-to-end convolutional neural network for 3D seismic fault segmentation." *Geophysics* 84.3 (2019): IM35-IM45.

[19] Lin, Chun Jin, and Shu Cai Li. "Tunnel seismic prediction (TSP) and its application in tunnel engineering." *Applied Mechanics and Materials*. Vol. 501. Trans Tech Publications Ltd, 2014.

[20] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *International Conference on Medical image computing and computer-assisted intervention*. Springer, Cham, 2015.

[21] Manthei, Gerd, and Jürgen Eisenblätter. "Acoustic emission in study of rock stability." *Acoustic emission testing* (2008): 239-310.

[22] Kong, Qingkai, et al. "Machine learning in seismology: Turning data into insights." *Seismological Research Letters* 90.1 (2019): 3-14.

[23] Metje, Nicole, et al. "Mapping the underworld–state-of-the-art review." *Tunnelling and underground space technology* 22.5-6 (2007): 568-586.

[24] Abouhamad, Mona, et al. "Corrosiveness mapping of bridge decks using image-based analysis of GPR data." *Automation in Construction* 80 (2017): 104-117.

[25] Liu, Bin, et al. "GPRInvNet: Deep Learning-Based Ground-Penetrating Radar Data Inversion for Tunnel Linings." *IEEE Transactions on Geoscience and Remote Sensing* (2021).

[26] Zhou, Cheng, et al. "Unsupervised spectral clustering for shield tunneling machine monitoring data with complex network theory." *Automation in Construction* 107 (2019): 102924.

[27] Gao, Xianjie, et al. "Recurrent neural networks for real-time prediction of TBM operating parameters." *Automation in Construction* 98 (2019): 225-235.

[28] Tsuruta, Ryosuke, Shinji Utsuki, and Masashi Nakaya. "Development of a System for Automatic Evaluation of the Geological Conditions of Tunnel Faces Using Artificial Intelligence and Application to a Construction Site." *IAEG/AEG Annual Meeting Proceedings, San Francisco, California, 2018-Volume 4*. Springer, Cham, 2019.

[29] Giardina, Giorgia, et al. "Evaluation of InSAR monitoring data for post-tunnelling settlement damage assessment." *Structural Control and Health Monitoring* 26.2 (2019): e2285.

[30] Anantrasirichai, Nantheera, et al. "Detecting Ground Deformation in the Built Environment using Sparse Satellite InSAR data with a Convolutional Neural Network." *IEEE Transactions on Geoscience and Remote Sensing* 59.4 (2020): 2940-2950.

[31] Zhang, Qianli, Zhenyu Liu, and Jianrong Tan. "Prediction of geological conditions for a tunnel boring machine using big operational data." *Automation in Construction* 100 (2019): 73-83.

[32] Feng, Dongming, and Maria Q. Feng. "Computer vision for SHM of civil infrastructure: From dynamic response measurement to damage detection–A review." *Engineering Structures* 156 (2018): 105-117.

[33] Yi, Cheng, et al. "Hierarchical tunnel modeling from 3D raw LiDAR point cloud." *Computer-Aided Design* 114 (2019): 143-154

[34] Cha, Young-Jin, et al. "Autonomous structural visual inspection using region-based deep learning for detecting multiple damage types." *Computer-Aided Civil and Infrastructure Engineering* 33.9 (2018): 731-747.

[35] Fujino, Yozo, and Dionysius M. Siringoringo. "Recent research and development programs for infrastructures maintenance, renovation and management in Japan." *Structure and Infrastructure Engineering* 16.1 (2020): 3-25.

[36] Westoby, Matthew J., et al. "'Structure-from-Motion'photogrammetry: A low-cost, effective tool for geoscience applications." *Geomorphology* 179 (2012): 300-314.

[37] Wang, Mingzhu, and Jack CP Cheng. "A unified convolutional neural network integrated with conditional random field for pipe defect segmentation." *Computer-Aided Civil and Infrastructure Engineering* 35.2 (2020): 162-177.

[38] Zhao, Shuai, Dong Ming Zhang, and Hong Wei Huang. "Deep learning–based image instance segmentation for moisture marks of shield tunnel lining." *Tunnelling and Underground Space Technology* 95 (2020): 103156.