Climate-aware Resilience for Sustainable Critical and interdependent Infrastructure Systems enhanced by emerging Digital Technologies

Massive Open Online Course
Resilience, Sustainability & Digitalisation in Critical Infrastructure

Lecture 5 Digital technologies

Lecture Notes

This project has received funding from the Horizon Europe Programme under the Marie Skłodowska-Curie Staff Exchanges Action (GA no. 101086413).
Co-funded by the UK Research & Innovation, and the Swiss State Secretariat for Education, Research & Innovation.

Introduction

A Massive Open Online Course (MOOC) is a free, open, online course designed to offer a taste of higher education to learners from across the world. The University of Birmingham is delivering new MOOCs in partnership with FutureLearn. Delivered by world-class academics from the University of Birmingham and other partners of the HORIZON Recharged project (GA no. 101086413), the course enable learners worldwide to sample high-quality academic content via an interactive web-based platform from leading global universities, increasing access to higher education for a whole new cohort of learners.
The course is developed by senior academic staff and their content is reviewed regularly, taking into account student feedback.

This MOOC brings together world experts, including general audiences, aiming to provide training with life-long updates and professional development opportunities for general and specialised audiences. The MOOC contains all the necessary components of a university taught module, e.g. prerequisites, content and aims, learning outcomes, attributes for sustainable professional development (cognitive, analytical, transferable skills, professional and practical skills), expected hours of study, assessment patterns, units of assessment and reading list, warm-up sessions, with relevant podcasts and videos, lecture notes and recorded lectures, some of which will be tailored for general audiences. This open course will be available on futurelearn.com and on the project website.

These lecture notes are accompanying the seven lectures of the MOOC. Following is the MOOC description, which contains the outcomes, the aims per week and the learning activities. The latter include a combination of material acquisitions and discussions, investigations and production, practical examples and analysis of case studies, and a set of collaboration and discussion forum.

Outcomes

Lecture 5-Week 5
The aim of this week is to explore digital technologies' impact on infrastructure monitoring, covering data acquisition, processing, and modelling. Key objectives include understanding digitalization's influence on infrastructure lifecycle, categorizing technologies by application scope, examining remote sensing methods for data collection, and addressing challenges in assessing structural conditions through acquired data.

- Types of technologies, disparate source and types of data
- Algorithms and Model Updating (ML and CV)
- Digital modelling and Building information modelling
- Examples of use digital of technologies for assessment of infrastructure throughout the lifecycle.

Lecture 5. Digital technologies

Lecture 5
Massive Open Online Course
Resilience, Sustainability & Digitalisation in Critical Infrastructure

Digital technologies

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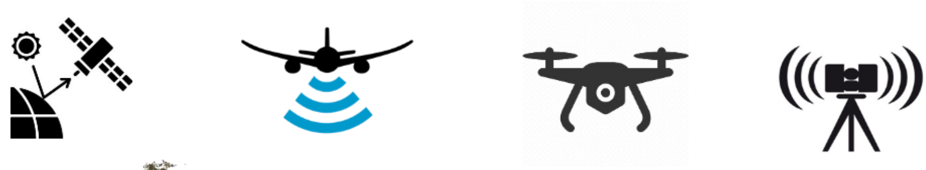
Lecture 5 Outcomes

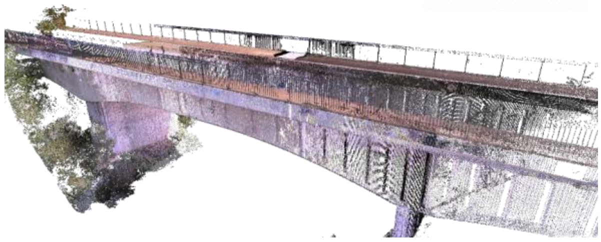
- Understand how digital technologies are employed in monitoring and inspection of infrastructure.
- Learn about the classes of digital technologies and understand the scope of their application.
- Understand how machine learning and computer vision can be employed to transform the way we design, construct and maintain our structures
- Learn what are Building Information Modelling and Digital Twins and their application for digital modelling of infrastructure.

Activity 1. Types of technologies and types of data

ACTIVITY 1: Types of Digital Technologies and Data (DT & Data)

- What is digital engineering?
- What is the value of data?
- Type of theologies for monitoring & assessment





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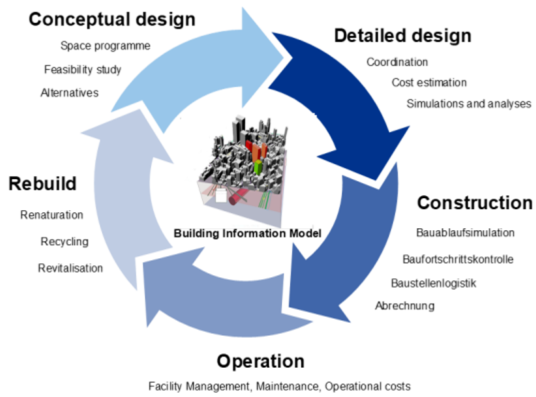
DT & Data: Digitalisation of infrastructure

Digital Engineering is the construction of digital (computer) models that represent characteristics of a complex product or system.

It involves application of digital technologies, processes, and methodologies over the lifecycle of infrastructure assets.

It leverages digital tools, software, and data-driven approaches to improve efficiency, accuracy, and collaboration.

Digital technologies include: Building Information Modelling (BIM), computer-aided design (CAD), virtual and augmented reality, data analytics, advanced simulation and visualization techniques.



The concept of Building Information Modeling (Borrmann *et al.*, 2018)

Available at: https://www.researchgate.net/publication/327759897_Building_Information_Modeling_Why_What_How_Technology_Foundations_and_Industry_Practice

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Digital Engineering is the construction of digital (computer) models that represent every characteristic of a complex product or system that is to be developed. Digitalisation of infrastructure involves application of digital technologies, processes, and methodologies in the design, construction, operation, and maintenance of infrastructure assets. It leverages digital tools, software, and data-driven approaches to improve efficiency, accuracy, and collaboration throughout the lifecycle of a project.

Digital technologies include: Building Information Modelling (BIM), computer-aided design (CAD), virtual and augmented reality, data analytics, and advanced simulation and visualization techniques. These tools enable engineers and other stakeholders to create and manage digital representations of structures and infrastructure, facilitating better decision-making, reducing errors and rework, improving coordination, and communication and enhancing the long-term performance and resilience of the built environment (Borrmann et al., 2018).

DT & Data: Digitalisation of infrastructure

The key aspects of digitalisation for structures and infrastructure include:

- **Modelling and Visualization** to understand the design and spatial relationships.
- **Collaboration and Coordination** among multidisciplinary teams through shared digital platforms and real-time data exchange.
- **Data Integration and Analysis** by integrating various data sources, including sensor data, geospatial information, and historical records.
- **Simulation and Analysis** to assess the structural integrity, energy efficiency, and environmental impact.
- **Construction and Asset Management** using automated machinery, drones for surveying and monitoring, and real-time progress tracking, as well as digital asset management systems for efficient maintenance, operation, and asset lifecycle management.

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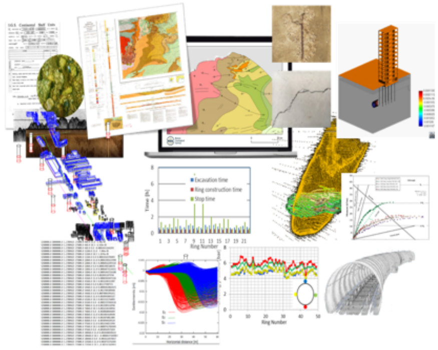
Digitalization of structures and infrastructure encompasses several key aspects. Modelling and Visualization are crucial for comprehending design and spatial relationships. Collaboration and Coordination are enhanced through shared digital platforms and real-time data exchange among multidisciplinary teams. Data Integration and Analysis combine various sources, including sensor data, geospatial information, and historical records, for comprehensive insights. Simulation and Analysis evaluate structural integrity, energy efficiency, and environmental impact. Construction and Asset Management leverage automated machinery, drones for surveying, real-time progress tracking, and digital asset management systems, ensuring efficient maintenance, operation, and overall lifecycle management of infrastructure assets.

DT & Data: Value of data

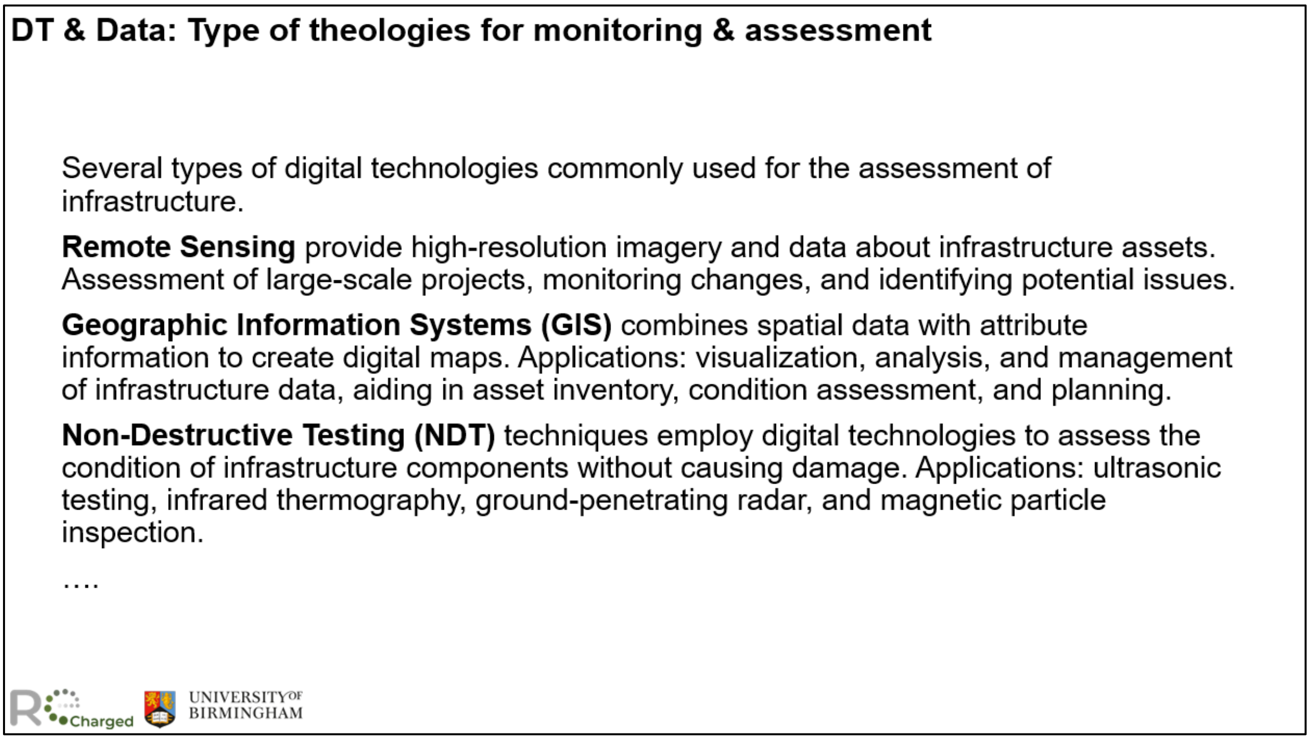
All data driven processes depend on both quality and quantity of data.

- **Quality** of the data will drive the accuracy and reliability of outcomes. High-quality data is accurate, complete, relevant, and up-to-date.
- Large **Quantity** of data will enhance the robustness and validity, statistical significance, and better identification of patterns and correlations.
- **Data collection and acquisition** processes must be suitable. This involves defining data requirements, selecting appropriate data sources, employing accurate measurement techniques, and utilizing reliable data collection tools or sensors



All data driven processes depend on both quality and quantity of data. Quality of the data will drive the accuracy and reliability of outcomes. High-quality data is accurate, complete, relevant, and up-to-date. Inaccurate or incomplete data can lead to flawed analyses, incorrect predictions, and suboptimal decision-making. Large Quantity of data will enhance the robustness and validity, enable more comprehensive analysis, statistical significance, and better identification of patterns, trends, and correlations. Large datasets can also help in training machine learning models for predictive analytics or optimization tasks.

To ensure an adequate quantity and quality of data, proper data collection and acquisition processes must be implemented. This involves defining data requirements, selecting appropriate data sources, employing accurate measurement techniques, and utilizing reliable data collection tools or sensors. And to monitor and inspect infrastructure we have number of available technologies.



Several types of digital technologies commonly used for the assessment of infrastructure.
Remote Sensing provide high-resolution imagery and data about infrastructure assets. These technologies are useful for assessing large-scale projects, monitoring changes, and identifying potential issues. Geographic Information Systems (GIS) combines spatial data with attribute information to create digital maps and models of infrastructure assets. It enables the visualization, analysis, and management of infrastructure data, aiding in asset inventory, condition assessment, and planning.
Non-Destructive Testing (NDT) techniques employ digital technologies to assess the condition of infrastructure components without causing damage. Examples include ultrasonic testing, infrared thermography, ground-penetrating radar, and magnetic particle inspection. NDT helps detect defects, cracks, corrosion, and other flaws in structures.

DT & Data: Type of theologies for monitoring & assessment

Structural Health Monitoring (SHM) systems use sensors to continuously monitor structures. SHM detects anomalies, predicts failures, and optimizes maintenance.

The Internet of Things (IoT) connects devices with sensors and embedded processing, providing real-time data, enabling continuous monitoring and condition-based maintenance.

Mobile applications for infrastructure assessment streamline data collection and reporting. Inspectors use apps to capture photos, record measurements, and input data.

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Structural Health Monitoring (SHM) systems use sensors like accelerometers, strain gauges, displacement sensors, and fiber optic sensors to continuously monitor structures. SHM detects anomalies, predicts failures, and optimizes maintenance. The Internet of Things (IoT) connects devices with sensors and embedded processing, providing real-time data on temperature, humidity, pressure, and vibration, enabling continuous monitoring and condition-based maintenance. Mobile applications for infrastructure assessment streamline data collection and reporting. Inspectors use these apps on smartphones or tablets to capture photos, record measurements, and input data, which is synchronized and accessible in real-time.

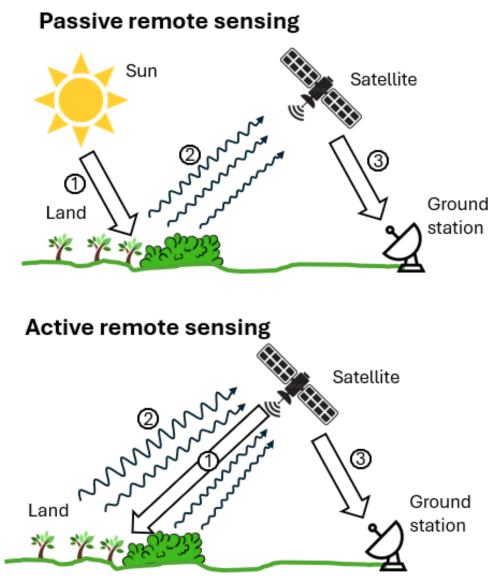
DT & Data: Remote sensing

Remote sensing is the acquisition of information about an object without making physical contact. It allows to capture, visualize, and analyse objects.

It uses satellite- or aircraft-based sensor technologies, along with ground-based devices, to detect and classify objects on Earth

There are two types of technologies

- "passive" remote sensing when the reflection of sunlight is detected by the sensor (e.g. optical, thermal and infrared)
- "active" remote sensing when a signal is emitted by source to the object and its reflection detected by the sensor (e.g. LiDAR, InSAR), and



https://wiki.aapg.org/Remote_sensing

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Remote sensing is the acquisition of information about an object without making physical contact, in contrast to in situ or on-site observation. It allows to capture, visualize, and analyse objects. It generally refers to the use of satellite- or aircraft-based sensor technologies to detect and classify objects on Earth.

There are two types of technologies, "passive" remote sensing when the reflection of sunlight is detected by the sensor (e.g. optical, thermal and infrared), "active" remote sensing when a signal is emitted by a satellite or aircraft to the object and its reflection detected by the sensor (e.g. LiDAR, InSAR) (Adamo et al., 2020; Sabins, 1998).

DT & Data: Geographic Information Systems (GIS)

- GIS is a framework for gathering, managing, analyzing and visualizing data.
- GIS reveals deeper insights into data, such as patterns, relationships, and situations—helping users make smarter decisions.
- GIS Includes
  - Maps,
  - data,
  - analysis,
  - applications.

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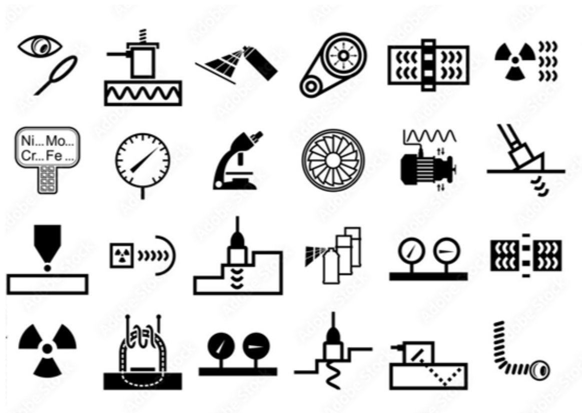
GIS is a framework for gathering, managing, analyzing and visualizing data. GIS reveals deeper insights into data, such as patterns, relationships, and situations—helping users make smarter decisions. GIS Includes: maps, data, analysis, applications.

Maps means geographic container for the data layers and analytics. Geographic data encompass imagery, features, and base maps that are integrated with spreadsheets or tables. These data are essential for the analysis and evaluation of suitability, capability, estimation, prediction, interpretation and understanding of data. Additionally, end users have access to applications that deliver a focused user experience for efficient task completion.

DT & Data: Non-Destructive Testing (NDT)

Non-destructive testing (NDT) is a set of techniques used to assess and evaluate the performance of structures without causing any damage to the infrastructure itself. It is essential for detecting defects, flaws, and potential issues in infrastructure.

Some common NDT methods used for infrastructure condition monitoring include: Ground Penetrating radar, ultrasonic testing, radiography, electromagnetic, magnetic and acoustic testing, etc.



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Non-destructive testing (NDT) plays a crucial role throughout the infrastructure lifecycle, from construction to maintenance and decommissioning. NDT techniques assess and evaluate the integrity, safety, and performance of structures without causing any damage. This is essential for detecting defects, flaws, and potential issues in infrastructure components early, preventing costly failures and ensuring long-term durability. Common NDT methods include Ground Penetrating Radar (GPR), ultrasonic testing, radiography, electromagnetic testing, magnetic testing, and acoustic testing. These methods provide critical data for making informed decisions, planning maintenance, and enhancing the safety and reliability of infrastructure systems, thereby optimizing lifecycle management and extending the lifespan of assets.

DT & Data: Non-Destructive Testing (NDT)

Ground Penetrating Radar (GPR) utilizes radar pulses to investigate the subsurface condition of materials or spaces, to detect voids, presence of discontinuities, etc.
Ultrasonic NDT (UT) -using high-frequency sound waves to identify changes in properties.
Radiography NDT (RT) - using gamma- or X-radiation on materials to identify imperfections.
Eddy Current NDT (ET) - electromagnetic testing that uses measurements of the strength of electrical currents in a magnetic field surrounding a material to assess the condition.
Magnetic Particle NDT (MT) - identifying imperfections in a material by examining disruptions in the flow of the magnetic field.
Acoustic Emission NDT (AE) - using acoustic emissions to identify possible defects
Dye Penetrant NDT (PT) - detects surface defects in non-porous materials by applying a liquid penetrant and developer to highlight flaws.

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The various Non-Destructive Testing (NDT) methods are distinguished by the principles they utilize and the types of defects or material conditions they are best suited to detect. Here's a comparison of each method based on their mechanisms, typical applications, and limitations.
Ground Penetrating Radar (GPR) utilizes radar pulses to investigate the subsurface condition of materials or spaces, to detect voids, presence of discontinuities, etc.
Ultrasonic NDT (UT) -transmitting high-frequency sound waves to identify changes in properties.
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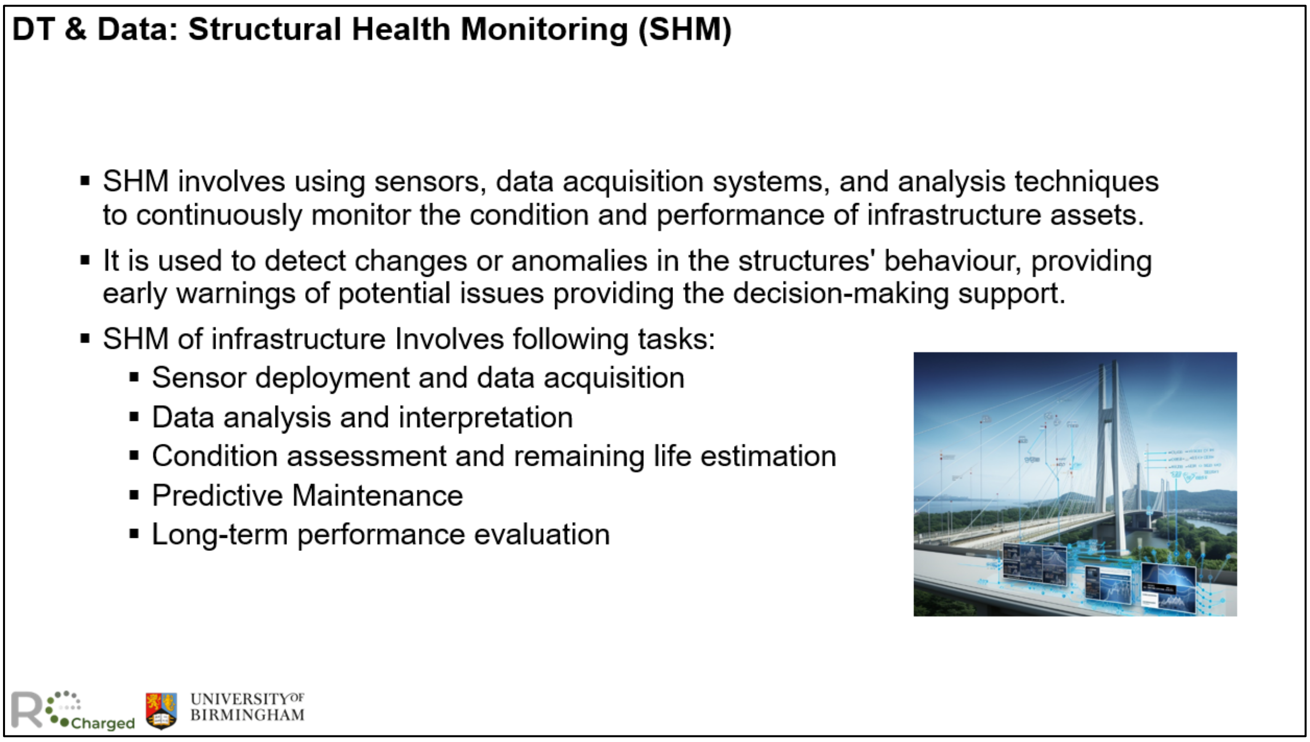
Eddy Current NDT (ET) - electromagnetic testing that uses measurements of the strength of electrical currents in a magnetic field surrounding a material to assess the condition, which may include the locations of defects.
Magnetic Particle NDT (MT) - identifying imperfections in a material by examining disruptions in the flow of the magnetic field
Acoustic Emission NDT (AE) - using acoustic emissions to identify possible defects and imperfections
Dye Penetrant NDT (PT) - detects surface defects in non-porous materials by applying a liquid penetrant and developer to highlight flaws.



Structural Health Monitoring (SHM) is a systematic process that involves using sensors, data acquisition systems, and analysis techniques to continuously monitor the condition and performance of infrastructure assets. The primary objective of SHM is to detect any changes or anomalies in the structures' behaviour and health, providing early warnings of potential issues and aiding in maintenance and decision-making. SHM involves several critical tasks; First, sensors are strategically deployed to collect data on stress, strain, vibration, and temperature. For example, strain gauges and accelerometers might be installed on key structural components. Next, this data is analyzed and interpreted to identify any anomalies or potential issues. Condition assessment then determines the current health of the structure, estimating remaining life based on detected wear and tear. Predictive maintenance uses this information to plan timely interventions, such as reinforcing weakened sections. Finally, long-term performance evaluation ensures the structure remains safe and functional over its lifespan, adjusting strategies as needed.

DT & Data: Internet of Things

The Internet of Things (IoT) refers to the integration of various smart devices, sensors, and communication technologies to collect and exchange data in real-time.

IoT enables infrastructure elements, such as, bridges, roads, water systems, and energy grids, to be connected and monitored digitally, providing valuable insights into their performance, condition, and usage.

Sensors and devices are deployed strategically throughout the infrastructure to measure parameters such as temperature, humidity, vibration, strain, pressure, flow rates.

The key components of IoT are:

- Sensors and devices for data collection
- Communication networks to transmit data from sensors to the central platform (e.g Wi-Fi)
- A central platform or dashboard collects and integrates data from different sensors
- Data analytics and cloud computing
- Decision support systems

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The Internet of Things (IoT) integrates smart devices, sensors, and communication technologies to collect and exchange data in real-time. This connectivity enables digital monitoring of infrastructure elements such as bridges, roads, water systems, and energy grids, providing valuable insights into their performance, condition, and usage.

Strategically deployed sensors measure parameters like temperature, humidity, vibration, strain, pressure, and flow rates. Key components of IoT include these sensors and devices for data collection, communication networks (e.g., Wi-Fi) to transmit data, a central platform or dashboard to integrate the data, and advanced data analytics and cloud computing for processing.

Decision support systems then use this analyzed data to provide actionable insights, enhancing infrastructure management efficiency and reliability. IoT thus transforms how we monitor and maintain infrastructure, paving the way for smarter, more responsive, and sustainable systems.

DT & Data: Internet of Things

- **The Internet of Things (IoT**) will provide new streams of input data, from different monitoring systems during contraction/operation
- This data will also feed back into design
- Digital construction will extend beyond the boundaries of project sites, linking BIM models to City Information Modelling (CIM) or "Smart City" systems.

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The Internet of Things (IoT) will generate valuable data from various monitoring systems during construction and operation. This data will refine designs, extending digital construction beyond project sites. By connecting BIM models to City Information Modelling (CIM) and "Smart City" systems, we enhance integration and efficiency across urban environments.

DT & Data: IoT vs SHM

The main difference between IoT and SHM is in their scope and focus:

Scope:

IoT for infrastructure monitoring is a broader concept that encompasses the integration of various smart devices and sensors into different types of infrastructure elements

SHM is a specialized subset of infrastructure monitoring that specifically targets the structural integrity and health of civil engineering structures. I.e. the scope of SHM is on the structural aspects of the infrastructure.

Focus:

The primary focus of IoT for infrastructure monitoring is to gather real-time data from various sensors deployed throughout the infrastructure to provide insights into its overall performance, condition, and usage. The main focus of SHM is to continuously monitor and assess the structural condition of a specific asset or component.

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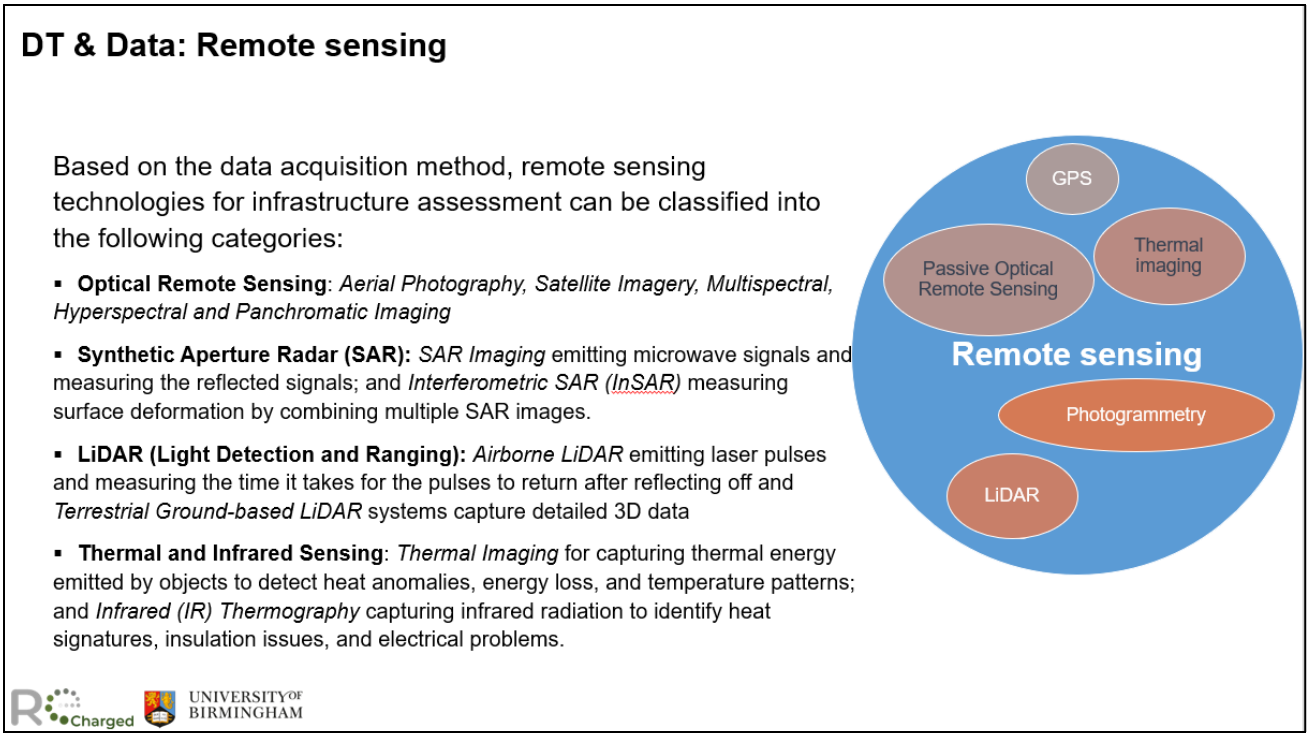
The main difference between IoT and Structural Health Monitoring (SHM) lies in their scope and focus. IoT for infrastructure monitoring is a broader concept that involves integrating various smart devices and sensors into different types of infrastructure elements. This allows for the collection of real-time data, providing comprehensive insights into the overall performance, condition, and usage of the infrastructure.

On the other hand, SHM is a specialized subset of infrastructure monitoring that specifically targets the structural integrity and health of civil engineering structures. Its scope is primarily on the structural aspects, focusing on continuously monitoring and assessing the condition of specific assets or components.

While IoT covers a wide range of infrastructure elements, SHM's main focus is on ensuring the structural safety and durability of individual structures. By concentrating on real-time data from sensors, IoT provides a holistic view of infrastructure performance, whereas SHM zeroes in on the critical task of maintaining structural integrity.



In the following, we will discuss more in detail about technologies for data collection sch as Remote sensing.

Based on the data acquisition method, remote sensing technologies for infrastructure assessment can be classified into the following categories: Optical Remote Sensing, Aerial Photography, Satellite Imagery, Multispectral, Hyperspectral and Panchromatic Imaging.

Synthetic Aperture Radar (SAR) imaging emitting microwave signals and measuring the reflected signals to create radar images; and *Interferometric SAR (InSAR)* measuring surface deformation by combining multiple SAR images.

Light Detection and Ranging (LiDAR) technologies such as Airborne, Spaceborne and Terrestrial LiDAR is emitting laser pulses and measuring the time it takes for the pulses to return after reflecting off objects to create highly accurate 3D models of infrastructure

Thermal Imaging is capturing thermal energy emitted by objects to detect heat anomalies, energy loss, and temperature patterns; and Infrared (IR) Thermography capturing infrared radiation to identify heat signatures, insulation issues, and electrical problems.

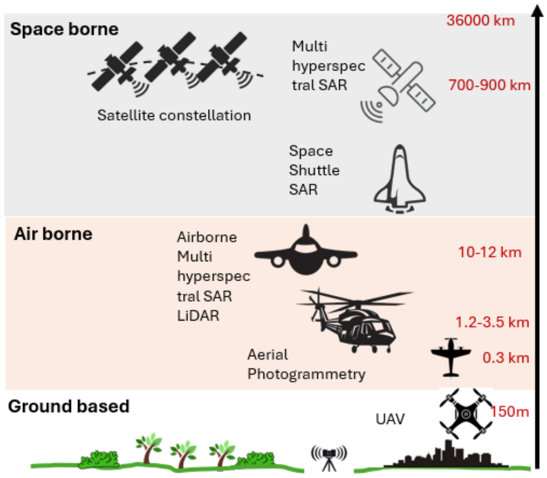
DT & Data: Remote sensing

Remote sensing technologies and their altitudes

Satellite Imagery:

- Low Earth Orbit (LEO) satellites: (160-2,000 km).
- Synthetic Aperture Radar (SAR) (200-2,000 km).

- **Unmanned Aerial Vehicles (UAVs) :(10-150 m).**
- **LiDAR:**
  - Airborne LiDAR: (200-5,000 m).
  - Terrestrial (Ground-based) LiDAR operate at close proximity to the infrastructure being monitored.
- **Infrared (IR) and Thermal** Imaging can be used on satellites, aircraft, or ground-based platforms, and their altitude depends on the specific platform and application.



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Remote sensing employs three main types of platforms: ground-based, airborne, and spaceborne. Currently, UAVs are extensively used in ground-based platforms, functioning at altitudes between 10 and 150 meters. Airborne platforms consist of helicopters, jet planes, and airplanes, which operate at altitudes from 0.3 to 12 kilometers. Spaceborne platforms involve sensors mounted on spacecraft or satellites that orbit the Earth, enabling them to capture images of the entire planet, typically operating at altitudes between 185 and 900 kilometers. As the platform's altitude increases, its coverage area expands, though this may result in a decrease in image quality. UAVs are particularly popular in the agricultural sector for a variety of remote sensing purposes. The types and operational heights of the different platforms used in remote sensing are detailed below.

DT & Data: Optical Remote Sensing

Optical Remote Sensing technologies include:

Aerial Photography, obtained from manned aircraft or unmanned aerial vehicles (UAVs), offers high-resolution images that enable detailed visual inspection and assessment of infrastructure.

High-Resolution Satellite Imagery, provides a bird's-eye view of infrastructure assets

Multispectral and Hyperspectral Imaging (MSI & HSI) capture images in various spectral bands, including visible, near-infrared, and sometimes additional spectral ranges.

Panchromatic and High-Resolution Imagery capture detailed grayscale or colour images with high spatial resolution.

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Optical remote sensing technologies are invaluable for infrastructure inspection and assessment. Aerial photography, whether from manned aircraft or UAVs, delivers high-resolution images for detailed visual inspections. High-resolution satellite imagery offers a comprehensive bird's-eye view of infrastructure assets, enhancing large-scale monitoring.

Multispectral and hyperspectral imaging (MSI & HSI) capture images across various spectral bands, including visible and near-infrared, revealing material properties and environmental conditions not visible to the naked eye. Additionally, panchromatic and high-resolution imagery provide detailed grayscale or color images with high spatial resolution, ideal for precise mapping and analysis of infrastructure components

DT & Data: Photogrammetry

Photogrammetry is a technique within optical remote sensing that focuses on the measurement and extraction of accurate geometric information from overlapping images. It involves the analysis of photographs or digital images to determine the shape, position, size, and other spatial properties of objects.

Photogrammetry utilizes the principles of triangulation and stereo vision to reconstruct the 3D geometry of objects from multiple images taken from different positions or angles.

While **Optical Remote Sensing** encompasses a broader range of technologies for data acquisition **Photogrammetry** focuses specifically on the geometric analysis and measurement of objects and surfaces using optical images.



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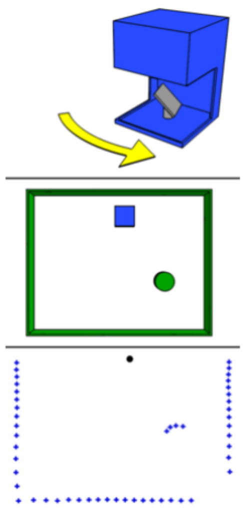
Photogrammetry, a key technique within optical remote sensing, specializes in extracting precise geometric information from overlapping images. By analyzing photographs or digital images, photogrammetry determines the shape, position, size, and spatial properties of objects. Utilizing principles of triangulation and stereo vision, it reconstructs the 3D geometry of objects from multiple images taken from various angles. While optical remote sensing broadly includes various data acquisition technologies, photogrammetry hones in on the geometric analysis and measurement of objects and surfaces through optical images, making it essential for detailed spatial studies and accurate 3D modeling.

DT & Data: LiDAR

- LiDAR (Light Detection and Ranging) operates by emitting laser light pulses and precisely timing how long they take to return after bouncing off the ground. It also measures the intensity of these reflections.
- LiDAR employs oscillating mirrors to emit laser pulses in multiple directions, creating a "sheet" of light. By measuring the timing and intensity of the returning pulses, it can gather data on objects such as terrain and structures.
- Other important features of LiDAR are:
  - high-precision satellite positioning system (GNSS
  - inertial measurement unit (IMU) high-accuracy sensors to determine the orientation of the LIDAR sensor in space



https://en.wikipedia.org/wiki/Lidar

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LiDAR (Light Detection and Ranging) operates by emitting laser light pulses and precisely timing how long they take to return after bouncing off the ground. It also measures the intensity of these reflections ("Lidar," 2024). LiDAR employs oscillating mirrors to emit laser pulses in multiple directions, creating a "sheet" of light. By measuring the timing and intensity of the returning pulses, it can gather data on objects such as terrain and structures.

DT & Data: LiDAR

LiDAR systems:

- **Airborne LiDAR** systems are mounted on aircraft or helicopters to collect data over large areas.
- **Terrestrial LiDAR** systems are ground-based and capture data by scanning the environment from a stationary or mobile position.
- **Mobile LiDARs** are typically mounted on vehicles, such as cars to capture data while driving along road networks and is combined with other positioning technologies, such as GPS to accurately georeferenced acquisition of data.
- **UAV-based LiDAR** sensors can be mounted on unmanned aerial vehicles (UAVs).

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LiDAR systems come in various forms, each suited to different applications, offering unique advantages in data collection and analysis. Airborne LiDAR systems, mounted on aircraft or helicopters, collect data over extensive areas, making them ideal for topographic mapping, environmental monitoring, and large-scale surveys. For example, they can map forest canopies and coastal zones with high accuracy. Terrestrial LiDAR systems, stationed on the ground, capture detailed scans of the surrounding environment from fixed or mobile positions, providing high-resolution data for construction, urban planning, and heritage site documentation. Mobile LiDAR systems, attached to vehicles like cars, gather data while moving along road networks, using GPS for precise georeferencing. These systems are crucial for creating detailed maps of urban infrastructure and transportation networks. UAV-based LiDAR sensors, mounted on unmanned aerial vehicles, offer flexible and efficient data collection for smaller or hard-to-reach areas. They are particularly useful for inspecting power lines, monitoring agricultural fields, and surveying disaster-stricken areas. Each form of LiDAR system brings specific benefits, enhancing the precision and efficiency of spatial data collection across diverse applications.

DT & Data: LiDAR vs Photogrammetry

LiDAR	Photogrammetry
Based on laser technology and the measurement of rebounding light points.	Employs an aligned series of digital images that overlap, as well as location data associated with pixels.
Produces high-density point clouds with precise distance measurements.	Generates 3D models, but its accuracy and point density depend on the quality of the images, camera calibration, and the number of overlapping images.
Signals can penetrate vegetation and other obstructions, making it suitable for mapping terrain and structures beneath dense vegetation canopies.	Relies on visible images and cannot penetrate obstacles.
Can be expensive to acquire and operate, especially for high-density data collection.	More cost-effective option, especially when utilizing existing aerial imagery or UAVs.

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LIDAR is a method based on laser technology and the measurement of rebounding light points. Photogrammetry employs an aligned series of digital images that overlap, as well as location data associated with pixels.
LiDAR produces high-density point clouds with precise distance measurements, while Photogrammetry can also generate 3D models, but its accuracy and point density depend on the quality of the images, camera calibration, and the number of overlapping images
LiDAR signals can penetrate vegetation and other obstructions, making it suitable for mapping terrain and structures beneath dense vegetation canopies, while photogrammetry relies on visible images and cannot penetrate obstacles.
LiDAR systems can be expensive to acquire and operate, especially for high-density data collection, while Photogrammetry can be a more cost-effective option, especially when utilizing existing aerial imagery or UAVs.

DT & Data: Challenges

The primary source of infrastructure condition data comes from visual inspections. Visual inspections are subjective, variable and non-reproducible. Some of the specific issues are:

- photographic evidence recorded and presented in an unsystematic manner
- difficulty in comparing photographs from successive inspections and hence comparing defect condition over time
- variation in practice between regional inspection teams
- inconsistent reliability of defect instance identification by inspectors
- a large range of possible defect types, which correlates with inaccurate defect classification

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Visual inspections are the primary method for assessing infrastructure conditions, but they have several limitations. These inspections are often subjective, varying between inspectors and lacking reproducibility. Specific issues include the unsystematic recording and presentation of photographic evidence, making it challenging to compare photographs from different inspections and track defect conditions over time. Practices can differ significantly between regional inspection teams, leading to inconsistent defect identification and reliability. Additionally, the wide range of potential defect types can result in inaccurate classification. These challenges highlight the need for more standardized and objective methods to improve infrastructure condition assessments.

DT & Data: Digital inspection of structures

Automated inspection framework consists of two main steps:

Utilizing optical sensing theologies for remote automated data acquisition;

Data processing and inspection using AI techniques

Created digital models to continuously store, manage and analyze collected data

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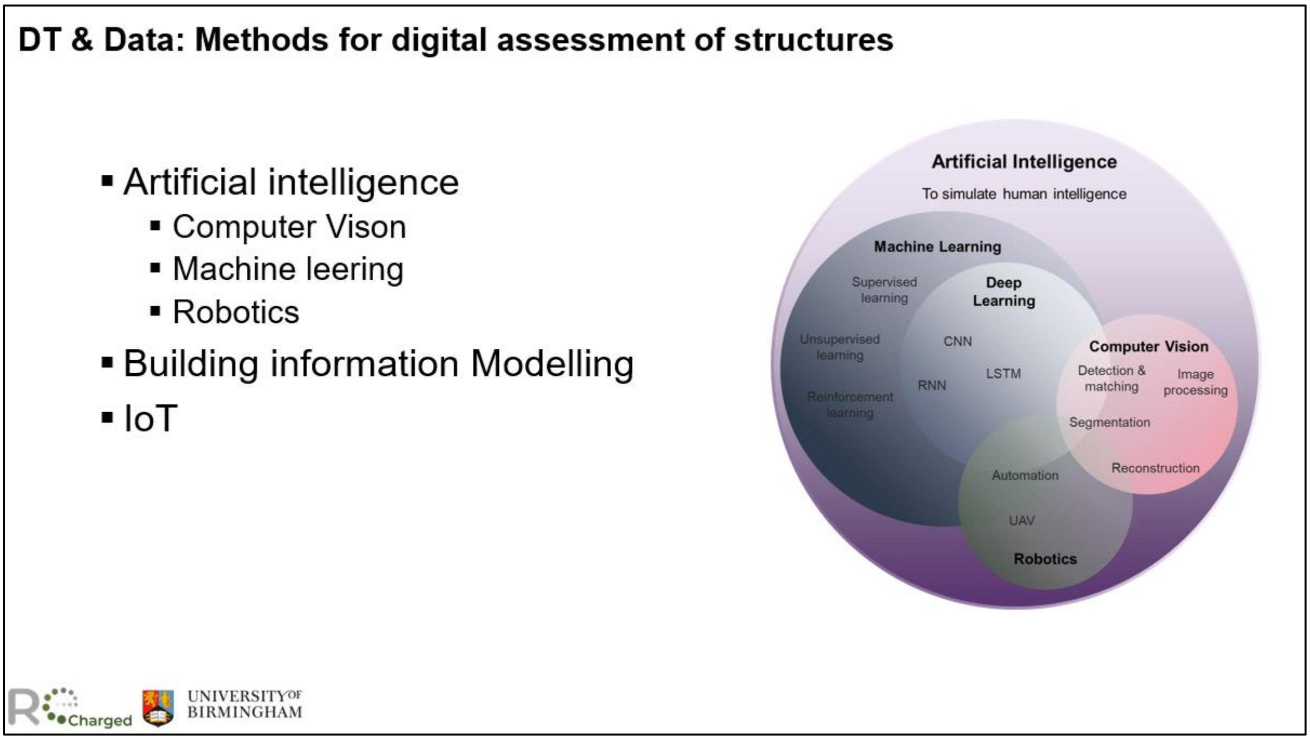
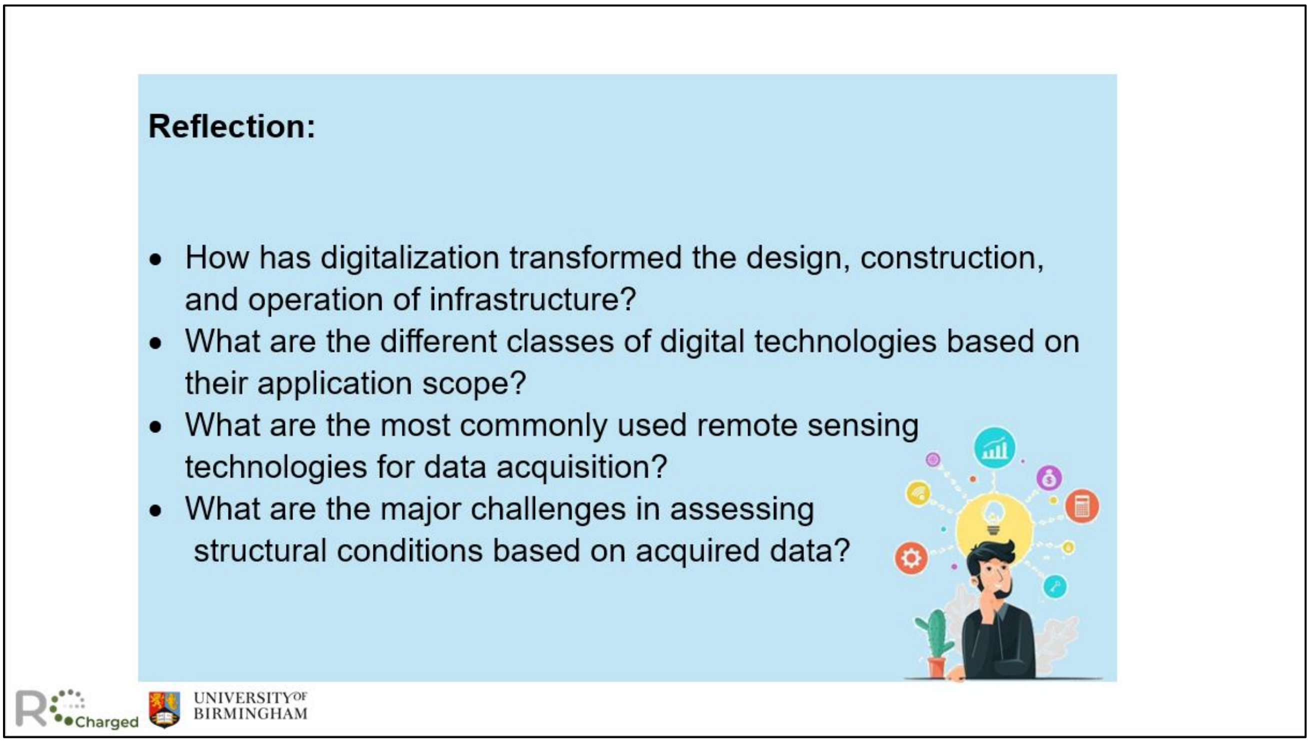
Digital inspection of structures is generally done within three steps. First step is utilizing optical sensing technologies for remote automated data acquisition. In the second step, data processing and inspection is conducted, and nowadays it's often supported using AI. Finally, in the third step, we can create digital models and continuously store, manage and analyze this collective data.



In modern infrastructure assessment, advanced technologies play a crucial role. Artificial Intelligence (AI) enhances predictive analytics and decision-making. AI generally encompasses three areas, Machine learning, Computer Vison and Robotics. Computer Vision automates visual data analysis for detecting structural anomalies. Machine Learning refines data analysis for precise predictions. Robotics automate physical inspections in hazardous areas. Building Information Modeling (BIM) integrates data into cohesive digital models for better planning and maintenance. The Internet of Things (IoT) provides real-time monitoring and alerts, ensuring proactive infrastructure management and safe (Huang et al., 2021).

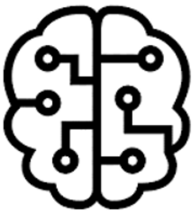


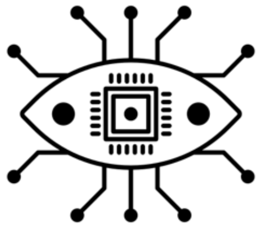
We have completed now our first activity on digital technologies and data types, talking about challenges as well as opportunities. At the end of this lecture you should reflect on how digitalization has transformed the design, construction and infrastructure. What are the different classes of digital technologies based on the application and scope? What are the most commonly used remote sensing technologies for the data and to reflect on your personal experience? What are the major challenges in assessing structural condition based on acquired data and what are the opportunities for the future and the areas you will be working on? To further leverage the power of digital technologies to improve the life cycle or the infrastructure.

Activity 2. Machine learning and Computer Vision for infrastructure lifecycle

ACTIVITY 2: Machine learning and Computer Vision (ML&CV)

- What is machine learning, and how is it applied in infrastructure lifecycle?
- What is Computer Vision and how is it applied for infrastructure inspections?





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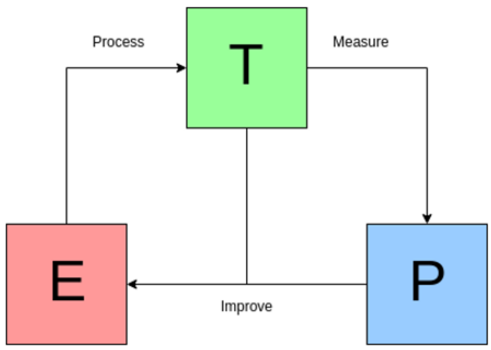
Within this activity we are going to answer following questions:
What is machine learning, and how is it applied in infrastructure lifecycle?
What is Computer Vision and how is it applied for infrastructure inspections?

ML&CV: Machine learning

"field of study that gives computers the ability to learn without being explicitly programmed" (Samuel, 1959) (Samuel, 1959)

"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."



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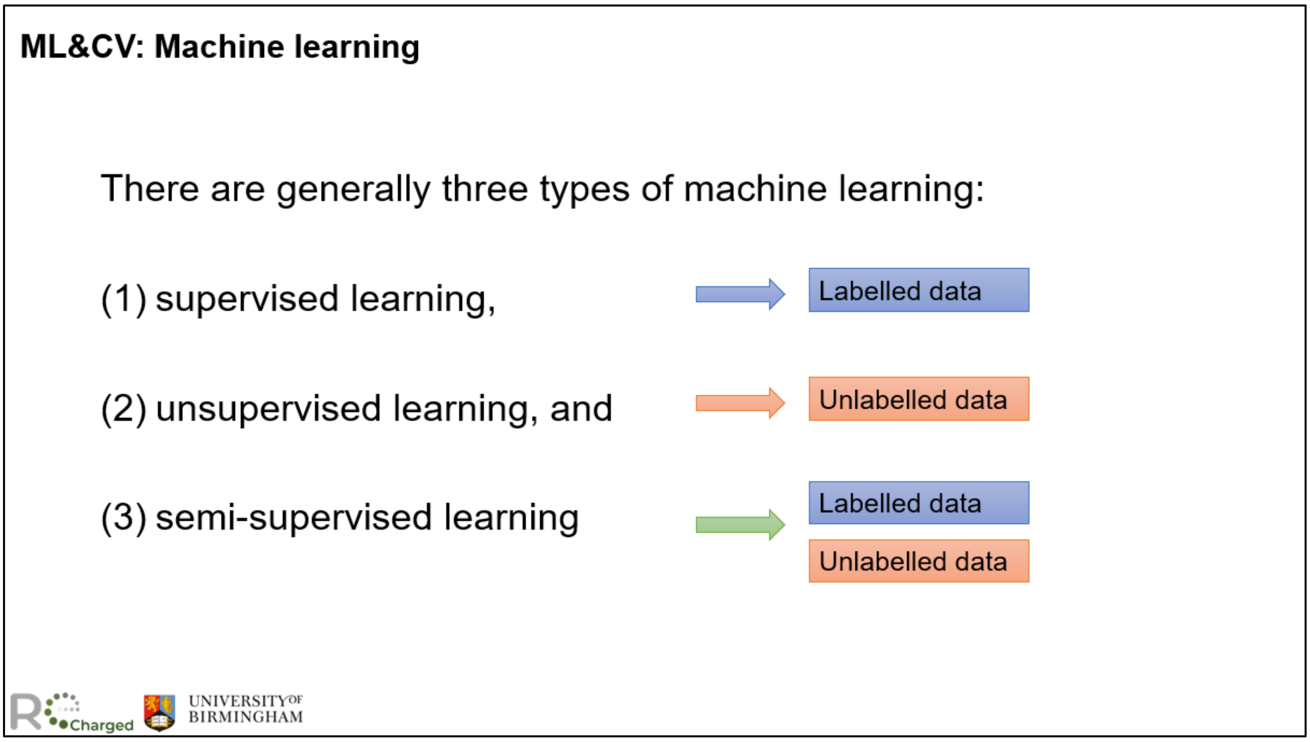
With a profound history that can be traced back to 1952 when Arthur Samuel developed the first game-playing program, machine learning was defined by the pioneer in 1959 as a "field of study that gives computers the ability to learn without being explicitly programmed" (Samuel, 1959). Machine learning algorithms are constructed to learn from data by automatically extracting patterns, with learning in this context defined by "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."(El Naqa and Murphy, 2015)

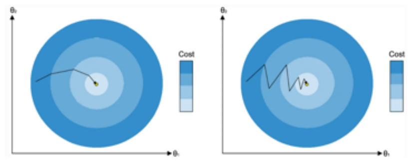


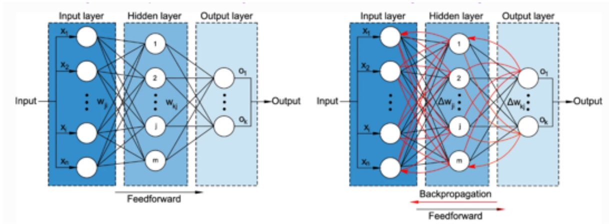
Machine learning typically falls into three categories: supervised learning, where models are trained on labeled data; unsupervised learning, which identifies patterns in unlabeled data; and semi-supervised learning, which combines both labeled and unlabeled data to improve model performance and accuracy. There is a fourth category of machine learning: reinforcement learning. The environment is typically stated in the form of a Markov decision process (MDP) atter do not assume knowledge of an exact mathematical model of the MDP and they target large MDPs where exact methods become infeasible ("Markov decision process," 2024).

ML&CV: Types of ML algorithms

Some supervised learning algorithms:

- Linear & Polynomial Regression
- Support Vector Machine
- k-Nearest Neighbours
- Decision Trees
- Neural Networks
- Random Forest
- Gaussian Processes





Cabrera et al. 2024
https://link.springer.com/article/10.1007/s00366-023-01864-1

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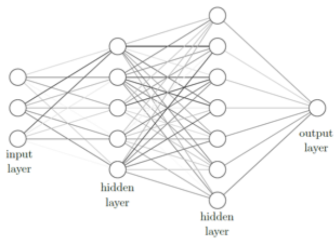
Supervised learning encompasses various algorithms designed to predict outcomes based on labeled data. Linear and Polynomial Regression are used for modeling relationships between variables. Support Vector Machines find optimal boundaries between classes. k-Nearest Neighbors classifies data based on proximity to known data points. Decision Trees make decisions through a tree-like model of choices. Neural Networks mimic brain function to handle complex patterns. Random Forest aggregates multiple decision trees for improved accuracy. Gaussian Processes use probabilistic methods to make predictions. Each algorithm offers unique strengths, making them suitable for different types of predictive tasks and data complexities (Cabrera et al., 2023).

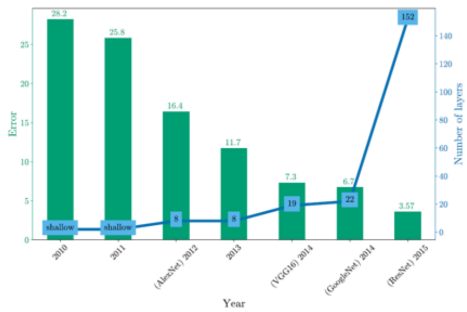
ML&CV: Types of ML algorithms

Deep neural network is a hierarchical organisation of more than one non-linear hidden layer, where the output of the previous layer serves as the input to the following layer



Deep learning has developed over the past decade in conjunction with several factors

- hardware development (GPU computing in particular),
- algorithm improvements
- and the availability of large training datasets.



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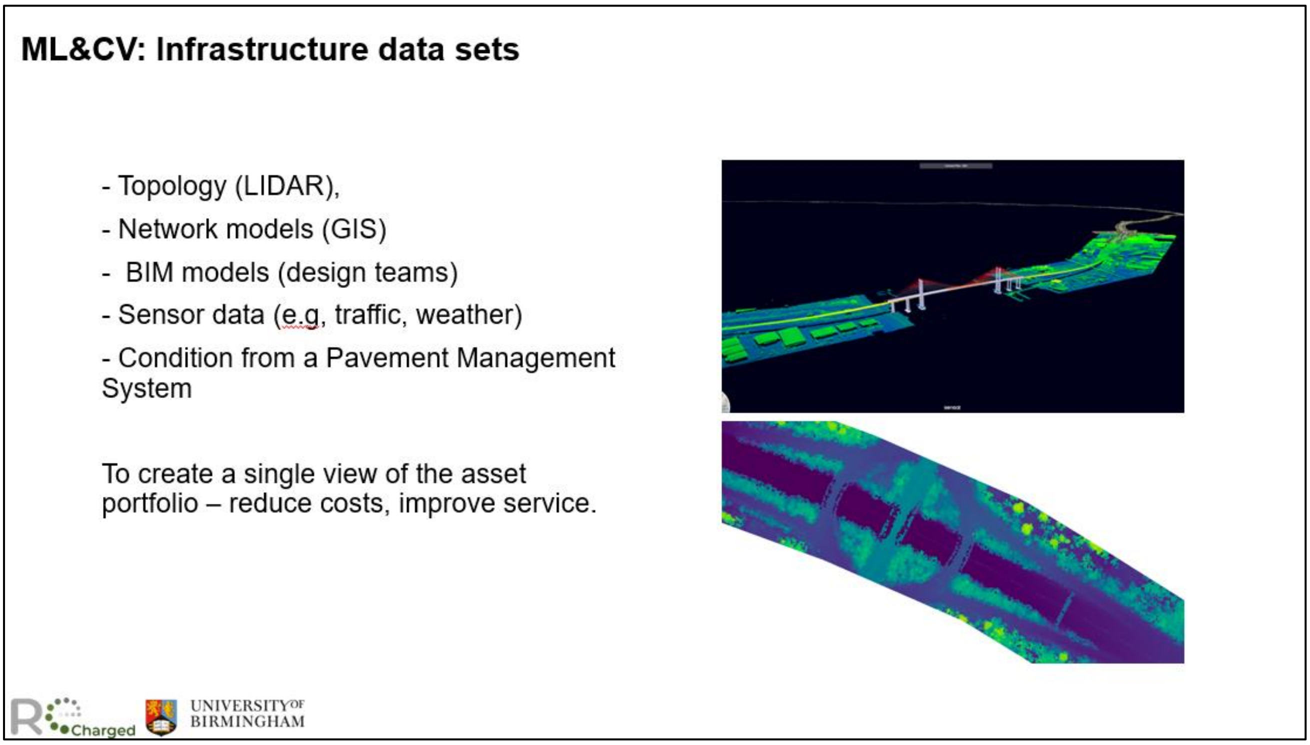
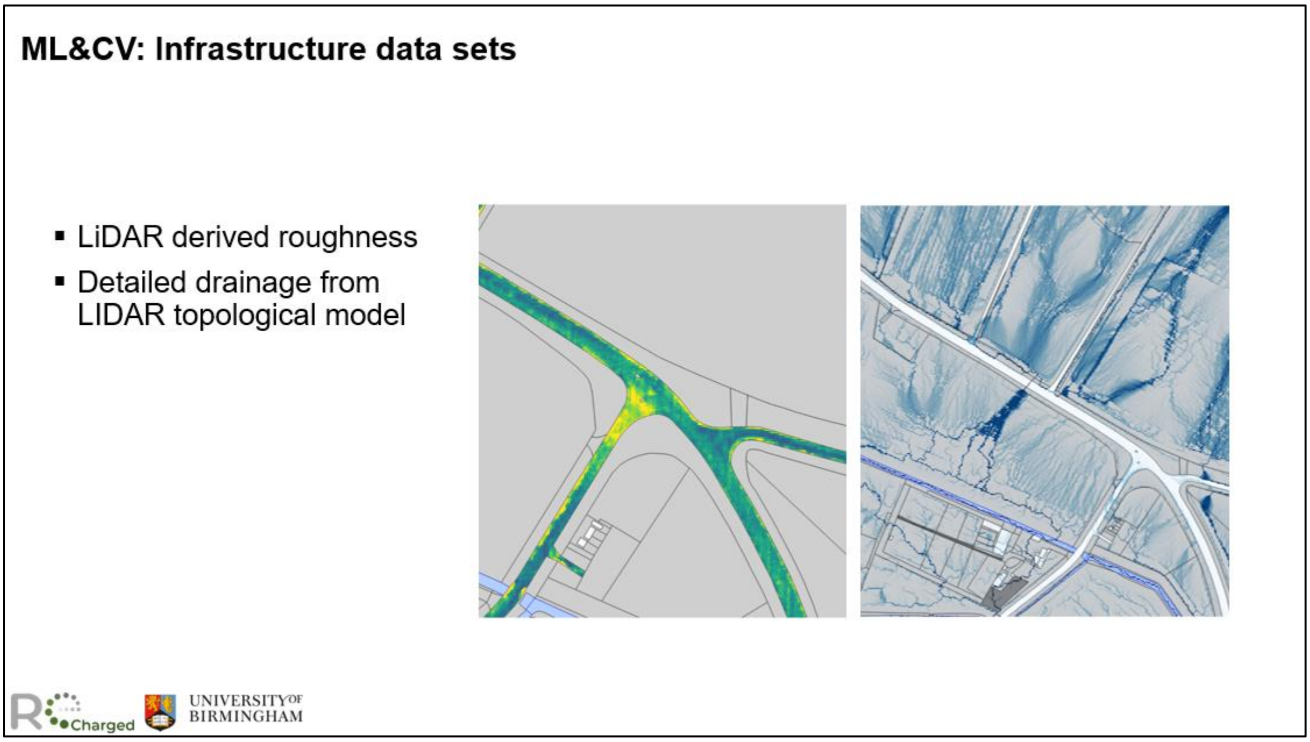
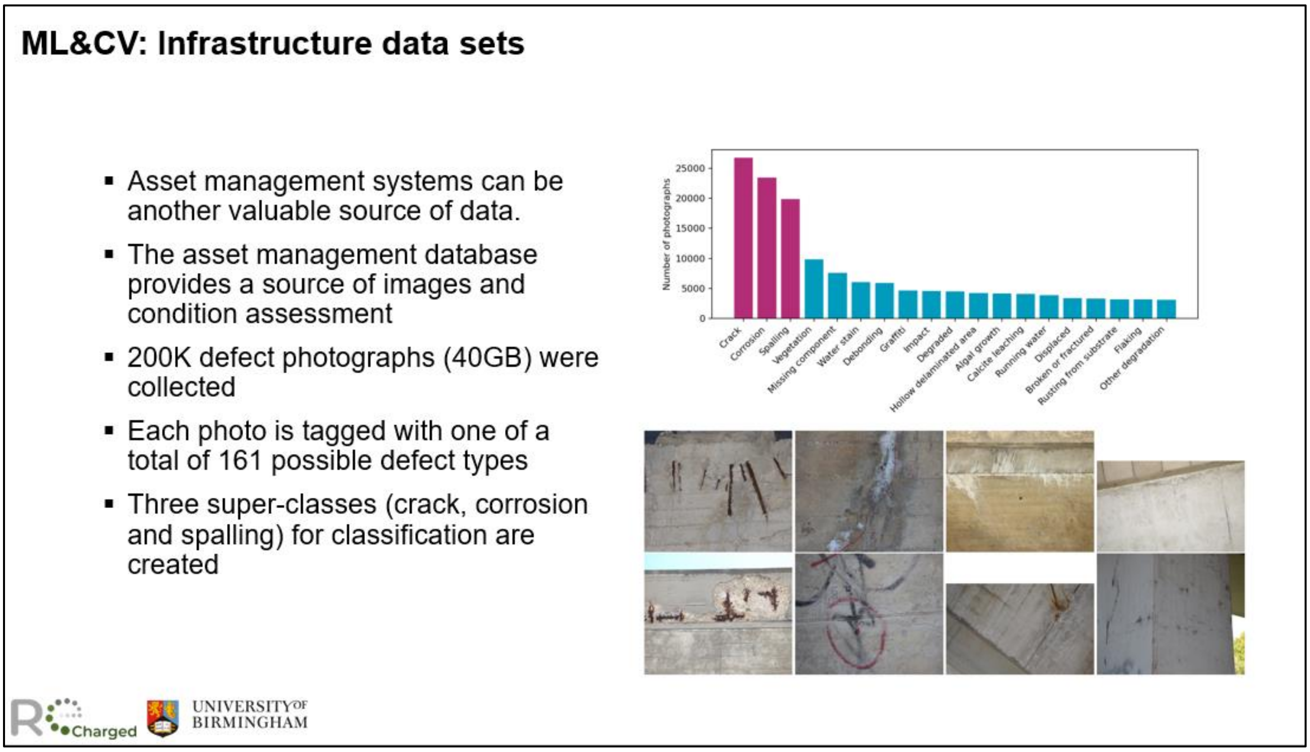
A deep neural network consists of multiple hierarchical layers, with each non-linear hidden layer's output feeding into the next. This architecture enables the network to learn complex patterns and representations. Deep learning, a subset of machine learning, has advanced significantly in the past decade due to several key factors: advancements in hardware, especially GPU computing, improvements in algorithms, and the availability of extensive training datasets. These developments have collectively enhanced the capability of deep neural networks to perform sophisticated tasks, such as image and speech recognition, and drive progress in various fields, from artificial intelligence to data science. The error rates of top performers at the LSVRC on ImageNet (Russakovsky et al., 2015), with the corresponding neural network's depth. We observe that from 2014 to 2015 a relatively small improvement is attained given the considerable increase in the number of layers.



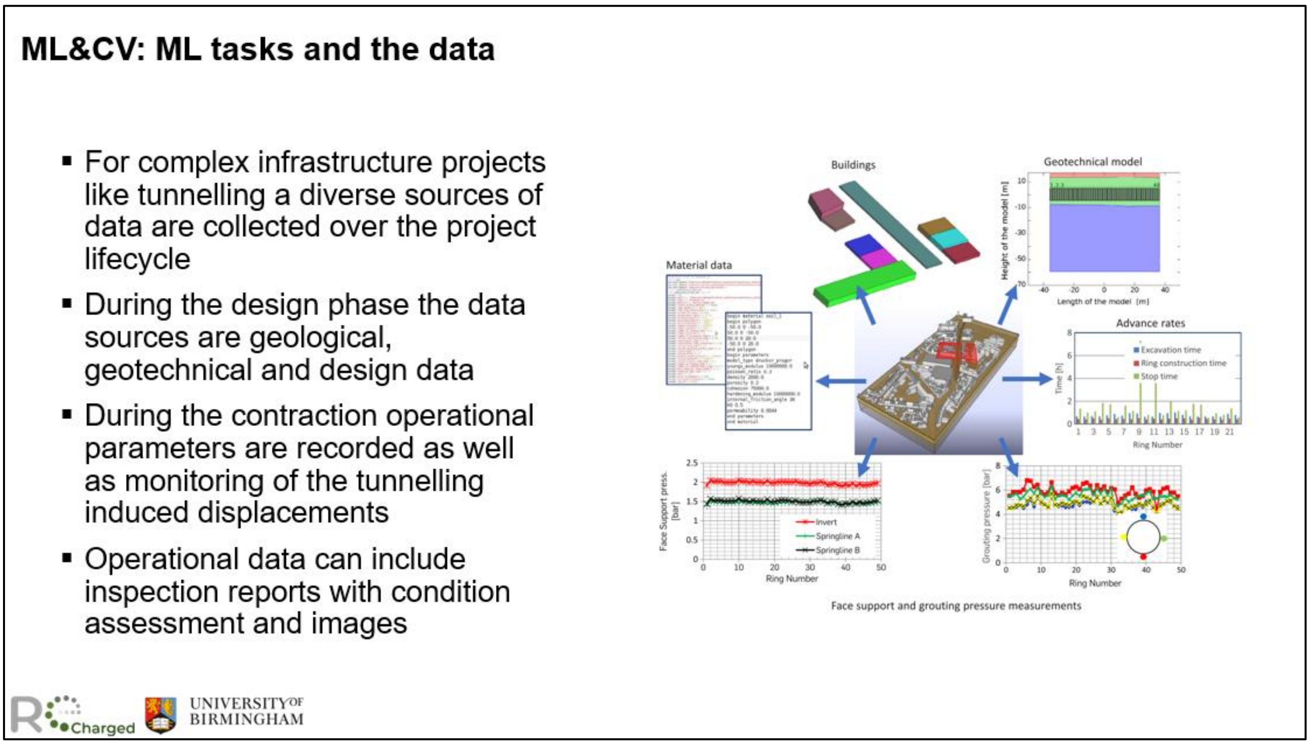
Infrastructure datasets encompass various types of information crucial for managing assets effectively. Topology data, obtained from LIDAR, provides detailed spatial information. Network models from GIS offer insights into the layout and connectivity of infrastructure. BIM models from design teams deliver comprehensive building information. Sensor data, such as traffic and weather conditions, provides real-time operational insights. Condition data from Pavement Management Systems tracks the state of road surfaces. Integrating these diverse datasets into a unified view enhances asset management by reducing costs and improving service quality, facilitating better decision-making and maintenance strategies (Corker et al., 2023).



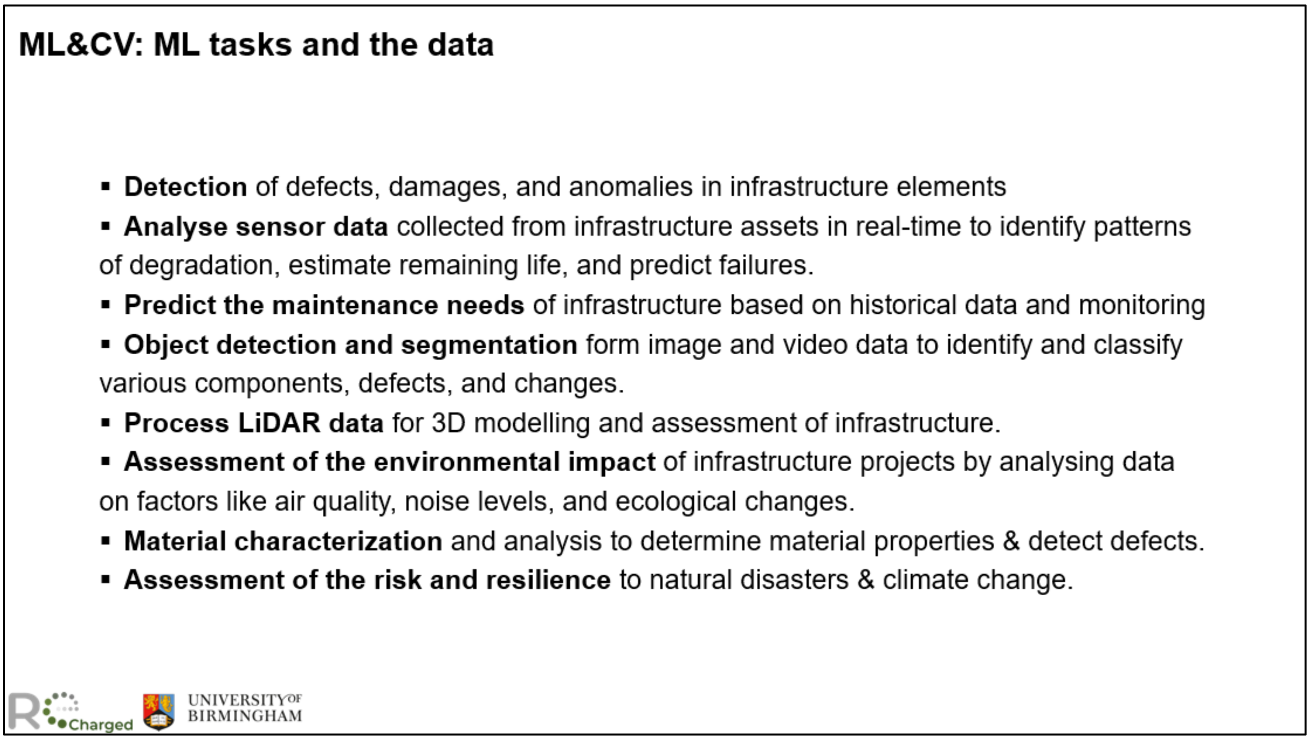
Pavement datasets include LiDAR-derived roughness measurements (Corker et al., 2023), which assess surface irregularities, and detailed drainage information from LiDAR topological models. These datasets provide critical insights into pavement conditions and drainage patterns, aiding in accurate assessment and effective maintenance, planning, and road infrastructure.



Asset management systems are crucial data sources for infrastructure management. For instance, the asset management database (Bush et al., 2021) offers extensive image and condition assessment data. The sown sample includes 200,000 defect photographs (Mundt et al., 2019), amounting to 40GB of information. Each image is tagged with one of 161 possible defect types, facilitating detailed analysis. Additionally, these defects are categorized into three super-classes—crack, corrosion, and spalling—to streamline classification and management processes. This structured approach enhances the ability to monitor, assess, and address infrastructure issues effectively, supporting better decision-making and maintenance strategies.



Complex infrastructure projects such as tunneling rely on diverse data sources (Ninić et al., 2017) throughout their lifecycle. During the design phase, crucial data includes geological, geotechnical, and design information, which helps in planning and engineering. In the construction phase, operational parameters are meticulously recorded, along with monitoring tunneling-induced displacements to ensure stability. Operational data also encompasses inspection reports that provide condition assessments and visual documentation of the infrastructure. This comprehensive data collection and analysis are essential for managing the project's progress, addressing potential issues, and ensuring the overall safety and effectiveness of the tunneling operations.

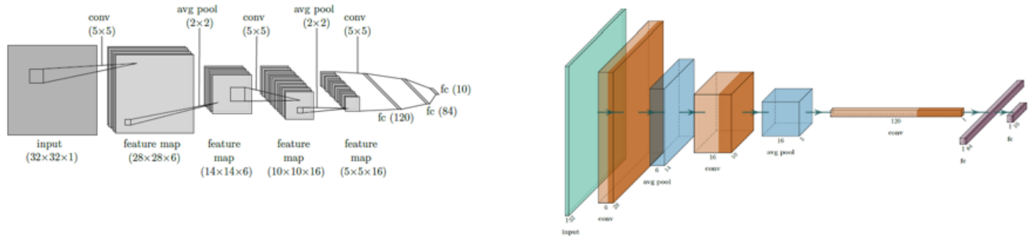


Machine learning significantly enhances infrastructure management by performing various critical tasks. Detection of defects, damages, and anomalies is achieved through advanced algorithms that process real-time sensor data to identify degradation patterns, estimate remaining lifespan, and predict potential failures. Predictive maintenance uses historical data and ongoing monitoring to forecast when maintenance will be required, optimizing resource allocation and reducing downtime. Object detection and segmentation of image and video data facilitate accurate identification and classification of infrastructure components, defects, and changes. LiDAR data processing supports detailed 3D modeling and assessment of infrastructure, improving visualization and planning. Furthermore, machine learning aids in assessing environmental impacts by analyzing data on air quality, noise levels, and ecological changes. Material characterization helps determine material properties and detect defects, while risk assessments evaluate the infrastructure's resilience to natural disasters and climate change, ensuring long-term safety and durability.

ML&CV: ML algorithms for image processing

Convolutional Neural Networks (CNNs) are currently dominating computer vision research. CNNs can be traced back to the early LeNet architecture.

- Visualising stacks of feature map channels is intuitive, however this representation becomes cumbersome for more complex networks.
- Extruded squares representation is a widely adopted convention
- Three fully connected (fc) layers in (left) is equivalent to the last convolutional (conv) layer in (right).



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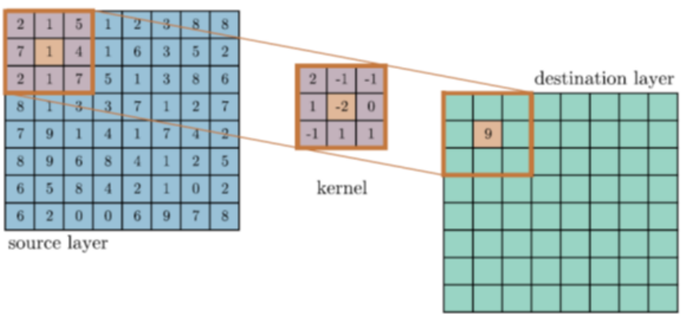
Convolutional Neural Networks (CNNs) are at the forefront of computer vision research, building on early architectures like LeNet (Lecun et al., 1998). While visualizing feature map channels is intuitive, it becomes unhandy for complex networks. The extruded squares representation has become a standard convention to simplify this visualization. Notably, three fully connected (fc) layers on the left side of the network are functionally equivalent to the last convolutional (conv) layer on the right, streamlining understanding and comparison.

ML&CV: CNN- convolution

- Convolution marked a step change in neural networks as it made the jump from tabular to image data computationally viable. The convolution operation applies a kernel to every pixel position in the source layer
- The output of convolution is the sum of element-wise multiplication of two matrices, and this is passed on to the corresponding pixel position in the destination layer

$$y_n = \sigma_n(\boldsymbol{w}_n^{\mathrm{T}} \boldsymbol{x}_n + \boldsymbol{b}_n)$$

$$y_n = \sigma_n(\mathrm{W}_n * \boldsymbol{x}_n + \boldsymbol{b}_n)$$



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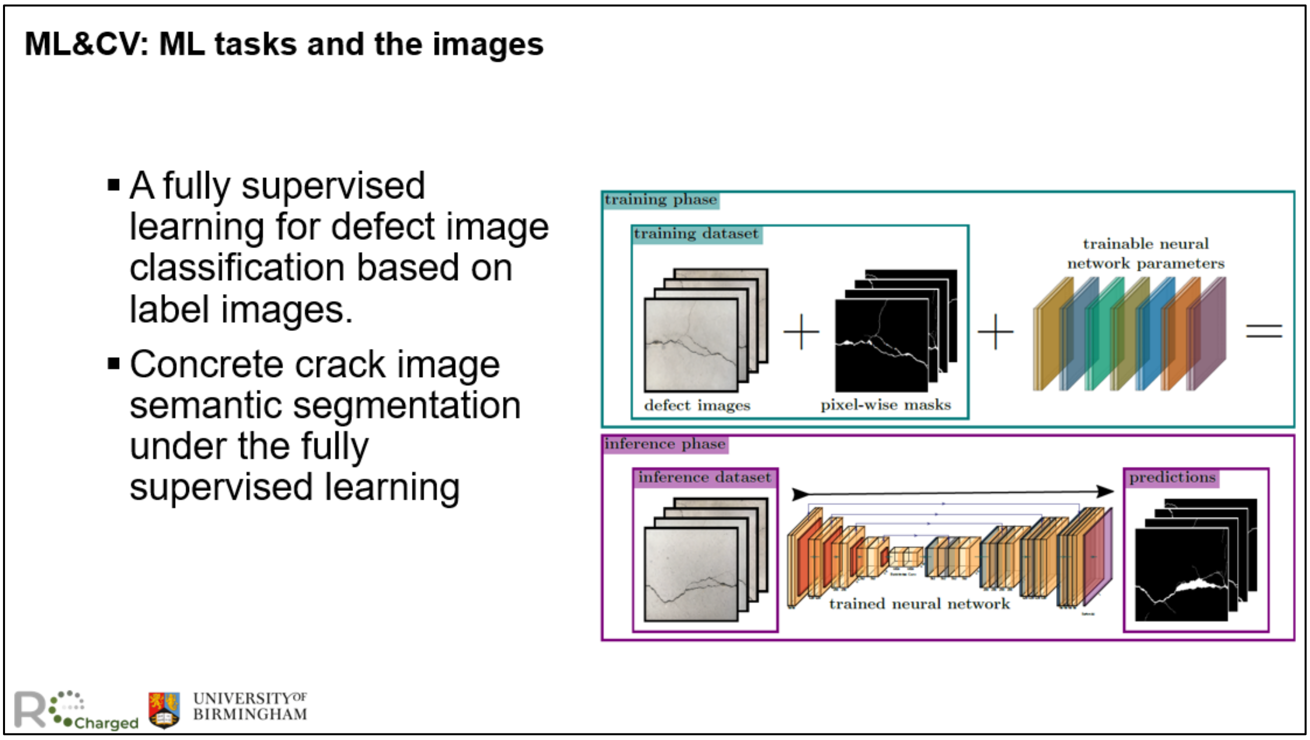
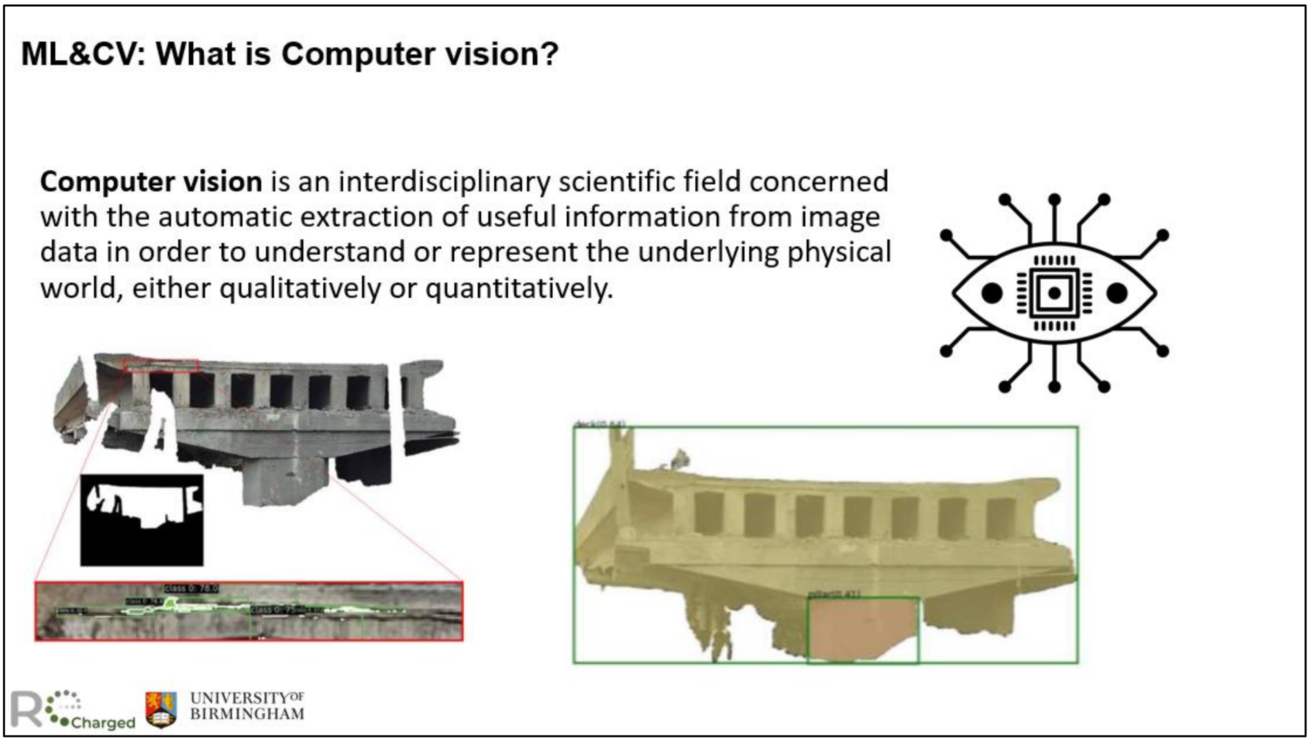
The introduction of convolution was a transformative advancement in neural networks. It enabled the processing of image data in addition to tabular data. Convolution operates by applying a kernel—essentially a small matrix—to each pixel position in the input layer. This process involves performing element-wise multiplication between the kernel and a region of the input image, then summing the results. The resulting value is then assigned to the corresponding pixel in the output layer. This method efficiently captures spatial hierarchies and patterns in images, making it a cornerstone of modern computer vision techniques and enhancing the capability of neural networks in image processing tasks.

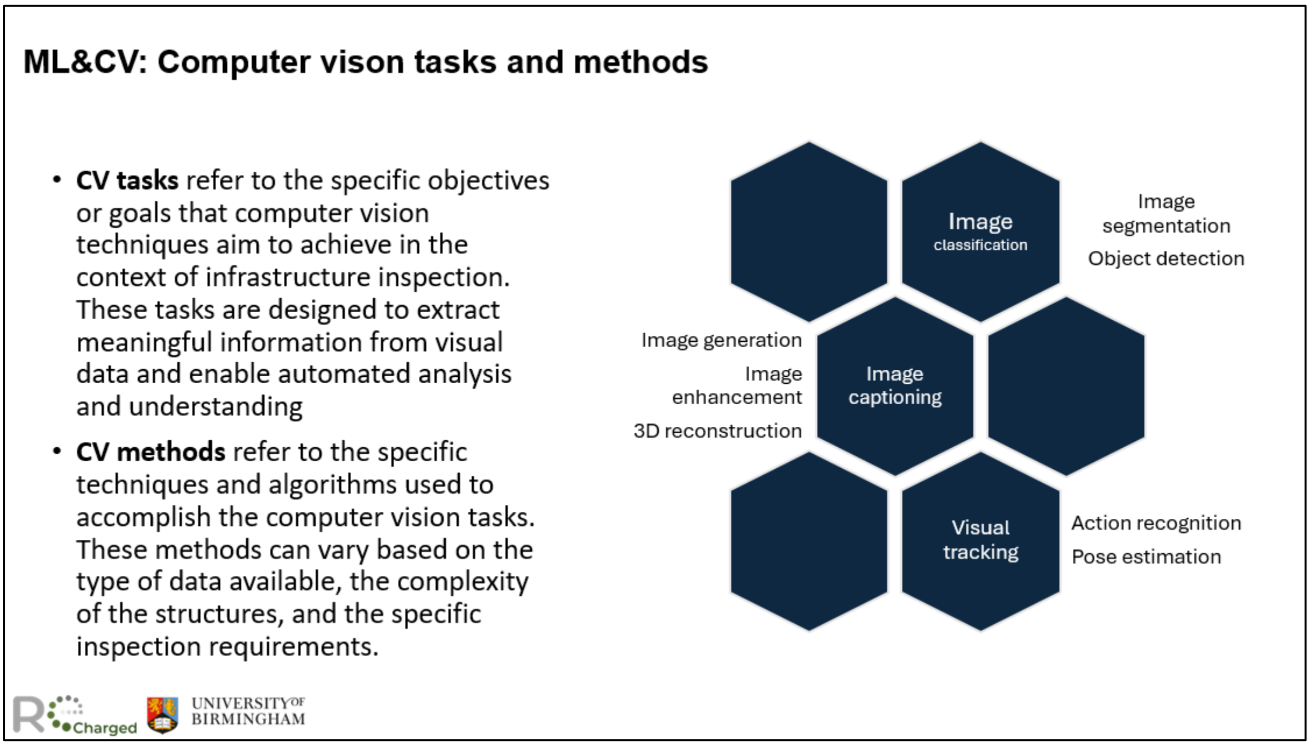


There are two common ML task that we can perform to learn form images:

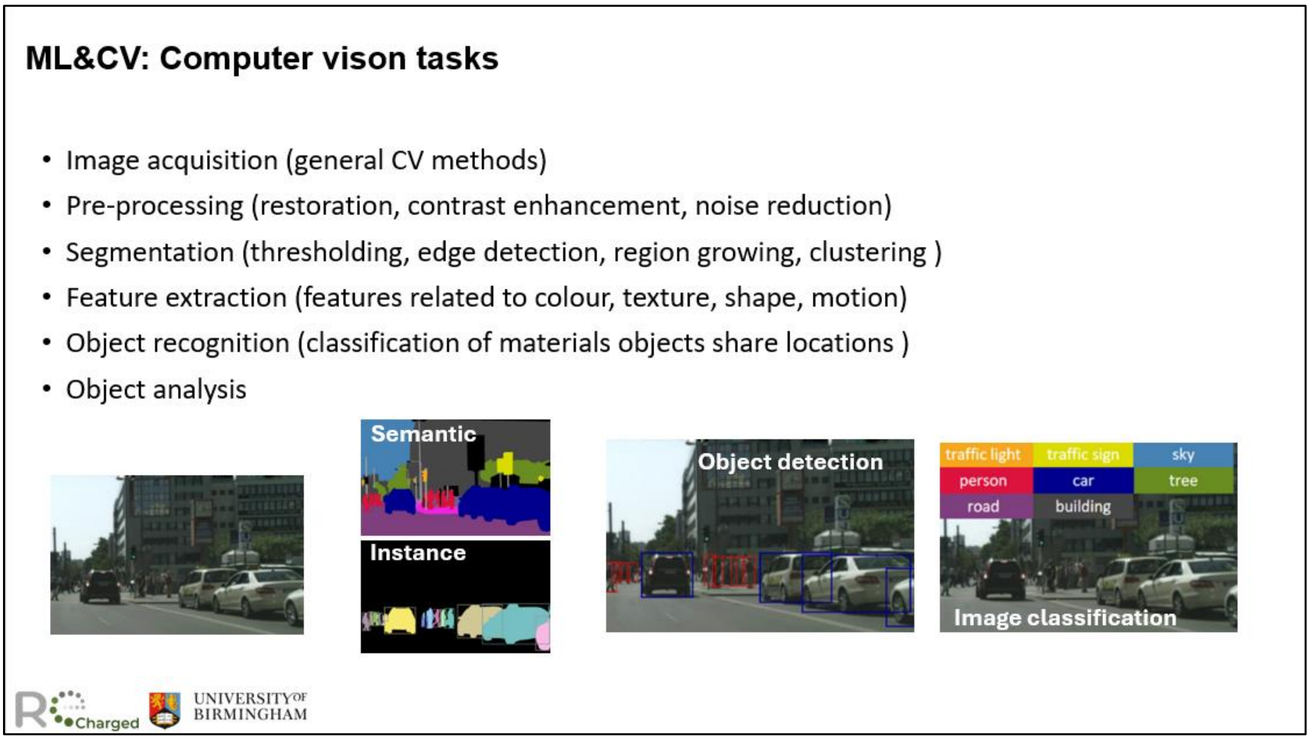
1. Multi-label prediction: Fully supervised learning tasks involve training models with labeled images to achieve high accuracy. For defect image classification, this approach enables precise identification of various defects by learning from annotated examples.
2. Semantic segmentation: In concrete crack image semantic segmentation, the model is trained to detect and segment cracks within images, classifying each pixel to delineate the cracks' exact boundaries. Both tasks require detailed, labeled datasets to ensure effective training and reliable performance in real-world applications.



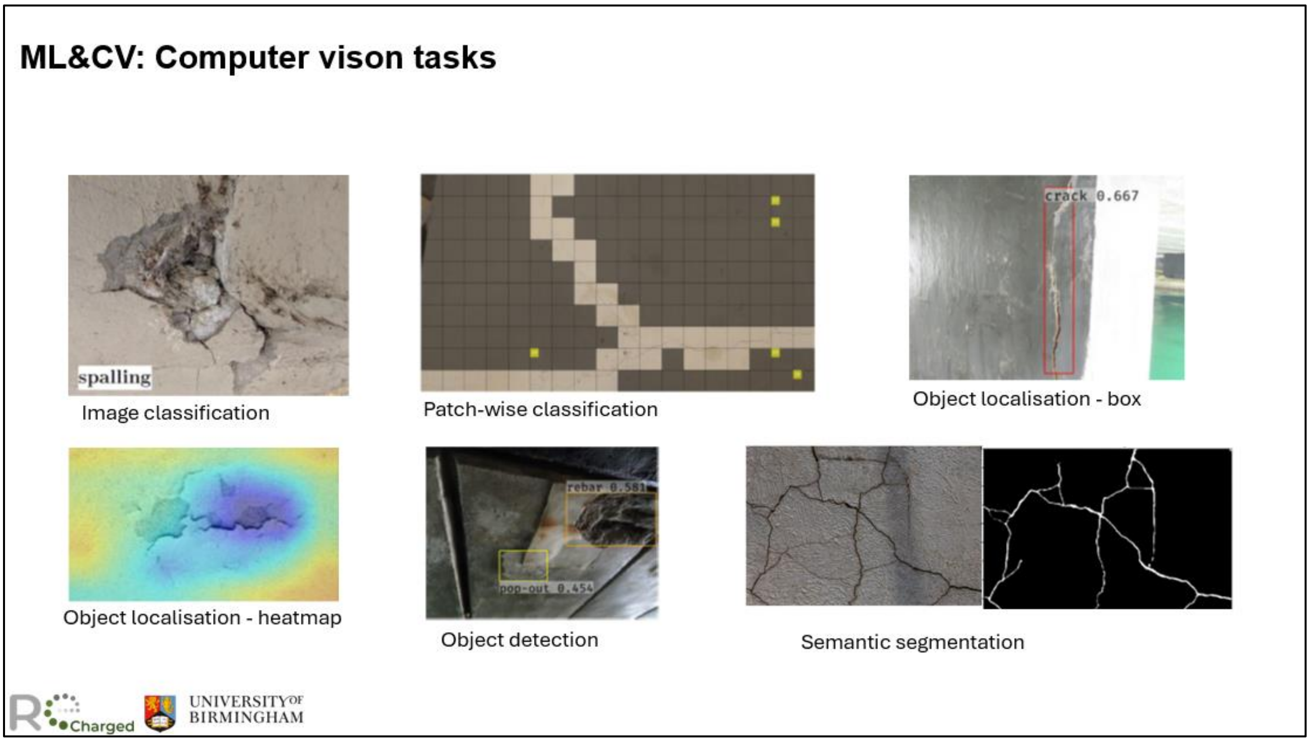
Computer vision (CV) is an interdisciplinary scientific field concerned with the automatic extraction of useful information from image data in order to understand or represent the underlying physical world, either qualitatively or quantitatively. CV should not be confused with Image Processing, where the output is the enhanced or compressed input image, although no understanding of the scene is gained.
In the image below on the expel of a bridge you can see how CV can be used for component detection and damage detection of bridges, but we will talk about this a bit more in detail, after we understand CV methods and tasks.



CV tasks in infrastructure inspection involve specific objectives aimed at extracting valuable information from visual data to facilitate automated analysis and understanding. These tasks are designed to address various inspection goals, such as detecting defects, assessing conditions, and identifying structural issues.
The CV methods employed to achieve these tasks include a range of techniques and algorithms tailored to the type of data, structural complexity, and inspection needs. These methods vary widely, from simple image processing techniques to advanced machine learning algorithms, each chosen to optimize performance based on the specific requirements of the inspection process.

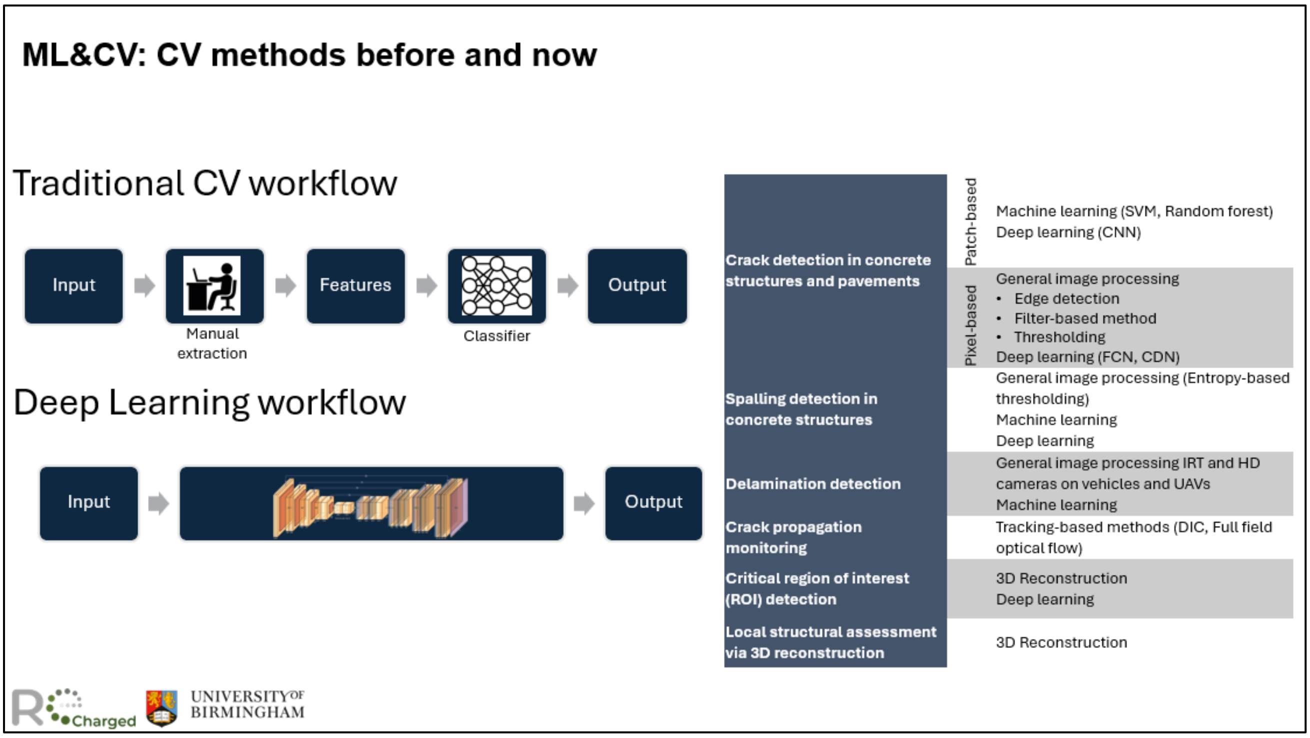


CV tasks in infrastructure inspection involve several critical stages. Image acquisition uses general CV methods to capture visual data from various sources. Pre-processing improves image quality through techniques such as restoration, contrast enhancement, and noise reduction. Segmentation divides images into meaningful regions using methods like thresholding, edge detection, and clustering. Feature extraction identifies key attributes related to color, texture, shape, and motion. Object recognition classifies and locates materials or objects within the image. Finally, object analysis evaluates these identified objects to assess their condition and relevance, facilitating comprehensive infrastructure inspection and maintenance.



We can apply computer vision techniques in industrial settings. The first example, depicted in the top left image, illustrates image classification, where the system categorizes the image as depicting spalling. The second example, shown in the adjacent top image, demonstrates patch-wise classification. In this approach, the image is divided into smaller segments, and each segment is classified to determine whether it contains a crack. The third image on the top demonstrates object localization, where a bounding box is drawn around a detected crack, and the system estimates the probability of the presence of the crack, which, in this case, is determined to be 66%. In the lower left corner, we observe object localization using a heatmap. This technique allows us to visualize which parts of the image the neural network considers significant for classification. By visualizing the synaptic weights of a trained neural network, we can determine the regions responsible for the classification decision. Additionally, by utilizing a gradient-weighted class activation mapping (Grad-CAM) heatmap, we can precisely localize differences within the image.

Next, the task of object detection is demonstrated, where the system is capable of identifying and detecting rebar within the image. Finally, the most complex task is semantic segmentation, which involves predicting labels for each pixel in the image. This pixel-wise classification identifies the specific class of each defect present in the image.



The traditional approach is to use well-established CV techniques such as feature descriptors (SIFT, SURF, BRIEF, etc.) for object detection. Before the emergence of DL, a step called feature extraction was carried out for tasks such as image classification. Features are small “interesting”, descriptive or informative patches in images. Several CV algorithms, such as edge detection, corner detection or threshold segmentation may be involved in this step. The development of CNNs has had a tremendous influence in the field of CV in recent years and is responsible for a big jump in the ability to recognize object. DL introduced the concept of end-to-end learning where the machine is just given a dataset of images which have been annotated with what classes of object are present in each image. Thereby a DL model is ‘trained’ on the given data, where neural networks discover the underlying patterns in classes of images and automatically works out the most descriptive and salient features with respect to each specific class of object for each object.

ML&CV: Computer vision methods

- **Image filtering** using methods such as Gaussian, Sobel, or Canny filters, to enhance edges, remove noise, and highlight relevant features in the images.
- **Image registration** by aligning multiple images or frames to account for differences in perspective or movement.
- **Feature detection and matching** to identify key points or features in images, such as corners or edges, and matching these features across multiple images to detect structural changes or movement.
- **Object detection and tracking** to locate and track specific objects or defects in images or videos.
- **Structural feature extraction**, to detect features, such as beams, columns, or joints, from images for further analysis and assessment.
- **Segmentation** for dividing the images into regions to isolate and analyze specific parts.
- **Texture analysis** of structures to detect surface anomalies or signs of wear and tear.

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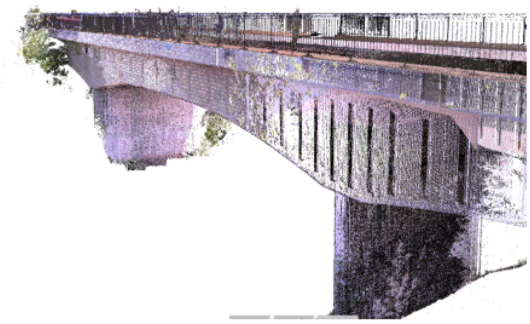
CV methods for infrastructure inspection involve several key techniques. Image filtering using Gaussian, Sobel, or Canny filters enhances edges, reduces noise, and highlights important features. Image registration aligns multiple images or frames to correct for differences in perspective or movement. Feature detection and matching identify key points, such as corners or edges, and track these across images to detect changes or movement. Object detection and tracking locate and monitor specific objects or defects in images or videos. Structural feature extraction identifies critical components like beams and columns for detailed analysis. Segmentation divides images into regions to isolate and examine specific parts, while texture analysis helps detect surface anomalies and signs of wear, providing crucial insights into the condition of infrastructure elements.

ML&CV: CV for 3D recontraction

Computer vision for 3D reconstruction is a set of techniques and algorithms that aim to create three-dimensional models of objects or scenes using multiple 2D images as input. This process is also known as "structure-from-motion" or "multi-view stereo.“

3D reconstruction from 2D images typically involves the following steps:

1. Feature Extraction
2. Feature Matching
3. Camera Pose Estimation
4. Triangulation
5. Bundle Adjustment
6. Surface Reconstruction



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Computer vision for 3D reconstruction is a set of techniques and algorithms that aim to create three-dimensional models of objects or scenes using multiple 2D images as input. This process is also known as "structure-from-motion" or "multi-view stereo.“ Feature extraction involves identifying key points, such as corners or edges, from each 2D image. These features serve as reference points for matching images. Feature matching establishes correspondences between features across different images using algorithms like nearest-neighbor or descriptor-based methods. Camera pose estimation determines the relative positions and orientations of cameras based on these correspondences, aligning images in 3D space. Triangulation calculates the 3D coordinates of matched points by intersecting rays traced back from each camera’s position. Bundle adjustment refines the 3D structure and camera poses by minimizing reprojection errors, considering calibration and noise. Finally, surface reconstruction processes the 3D points to create detailed surface representations, such as point clouds, meshes, or textured 3D models, depending on the application’s needs.

Feature Extraction: Key points or features are extracted from each 2D image, such as corners, edges, or distinctive regions. These features serve as reference points for matching between images.

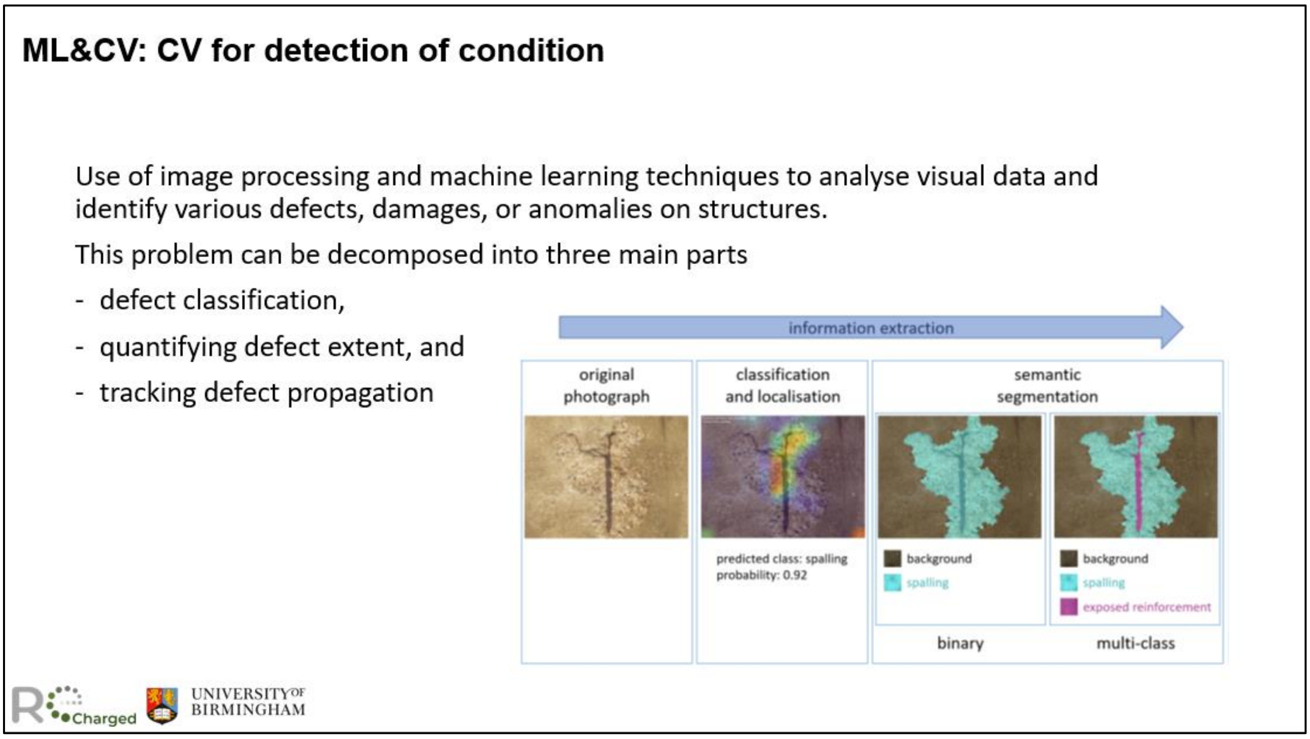
Feature Matching: Correspondences between the features across different images are established to identify the same points in multiple views. Various matching algorithms, such as nearest-neighbor or feature descriptor-based methods, are used for this purpose.

Camera Pose Estimation: The relative camera poses (positions and orientations) between the images are estimated based on the correspondences found in the previous step. This step determines how each image is related to the others in 3D space.

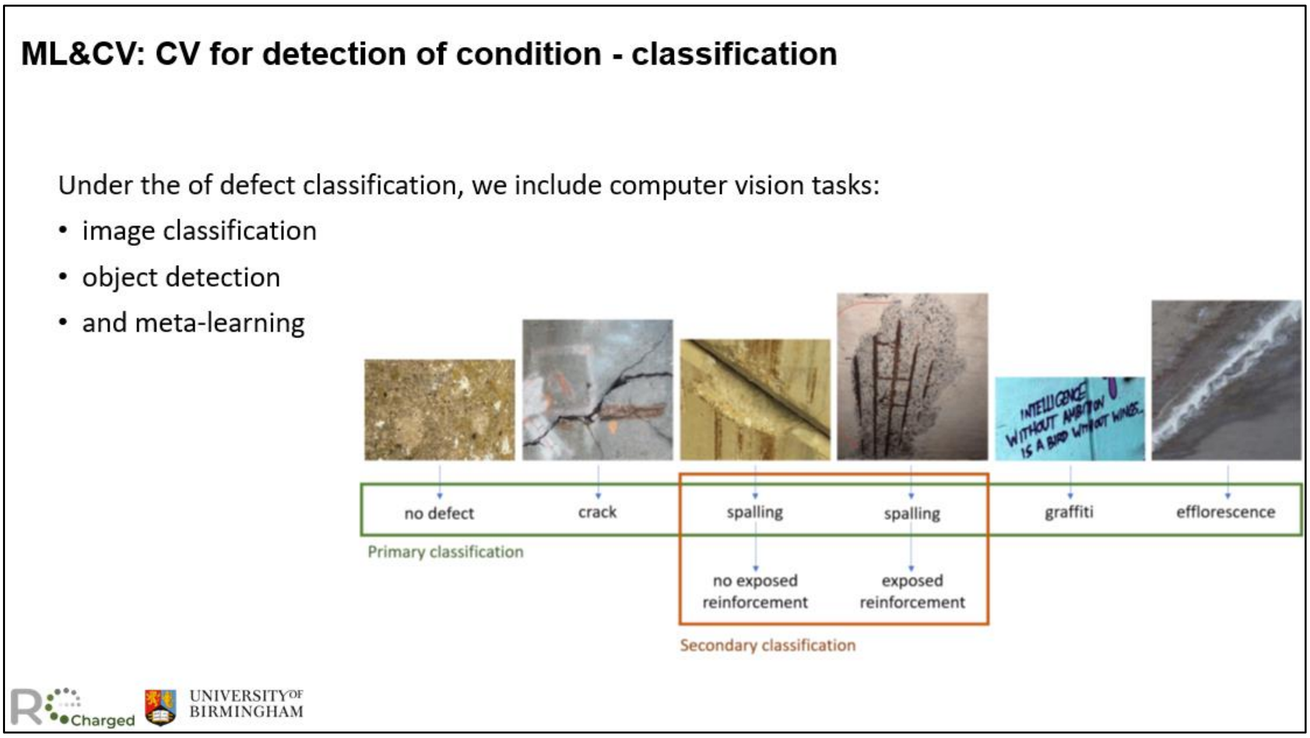
Triangulation: The 3D coordinates of the matched points are calculated using triangulation techniques. By intersecting the rays traced back from each camera's position through the matched points, their 3D positions are estimated.

Bundle Adjustment: An optimization process called bundle adjustment is performed to refine the 3D structure and camera poses. This step minimizes the reprojection errors between the 3D points and their corresponding 2D image projections, taking into account factors like camera calibration and noise.

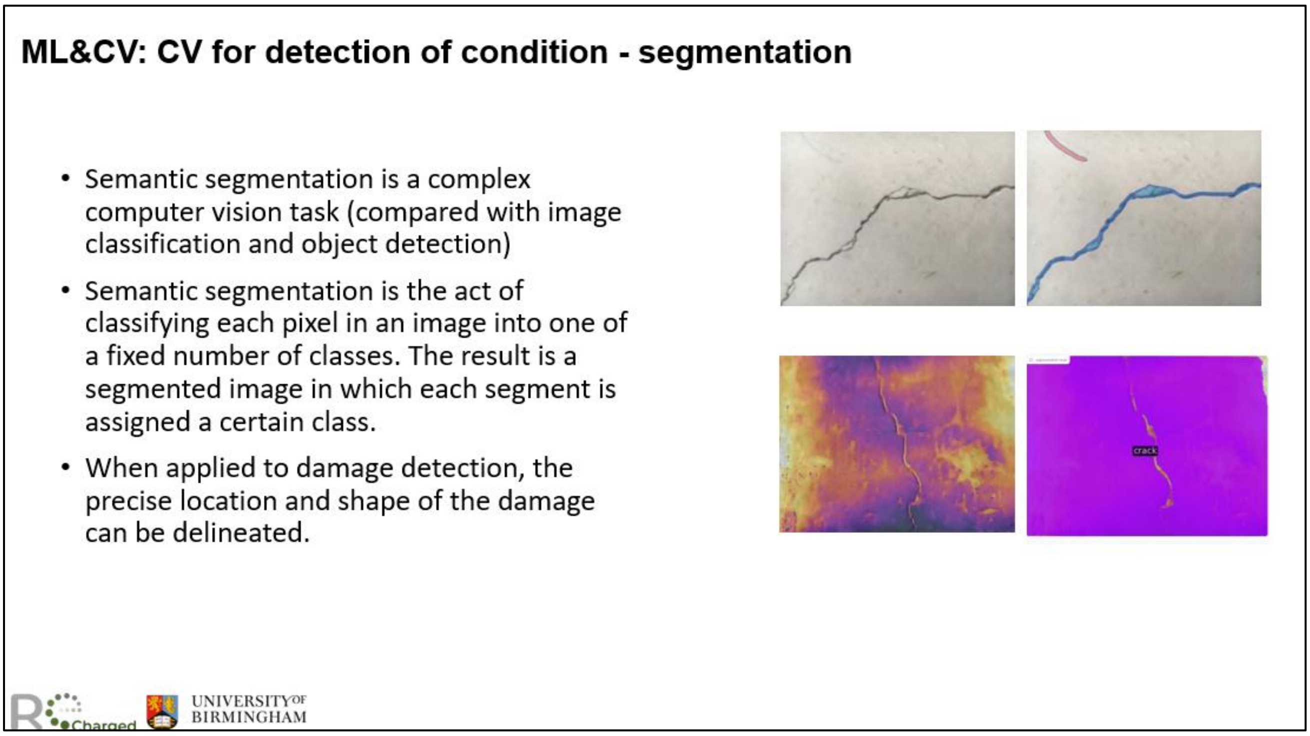
Surface Reconstruction: Depending on the application and level of detail needed, the 3D points can be further processed to generate a 3D surface representation, such as a point cloud, a mesh, or a textured 3D model.



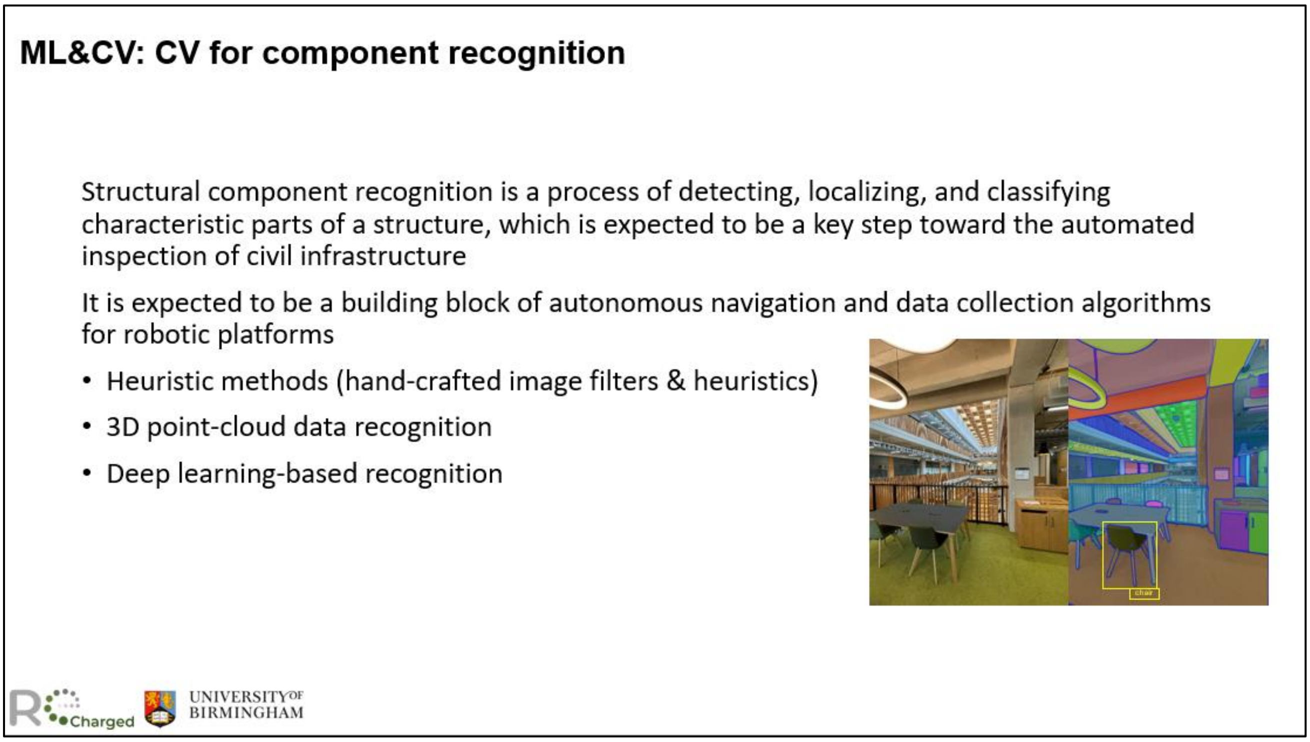
Semantic segmentation methods, like U-Net and FCN (Fully Convolutional Networks), CNN, can segment the images at the pixel level and classify each pixel into different classes. Instance segmentation techniques, such as Mask R-CNN, extend semantic segmentation to differentiate individual instances of objects within the same class. This is useful for distinguishing multiple occurrences of similar defects or components. Image processing and machine learning techniques analyze visual data to detect defects, damages, or anomalies in structures. This process can be divided into three main tasks: defect classification to identify the type of defect, quantifying defect extent to measure severity, and tracking defect propagation to monitor changes over time.



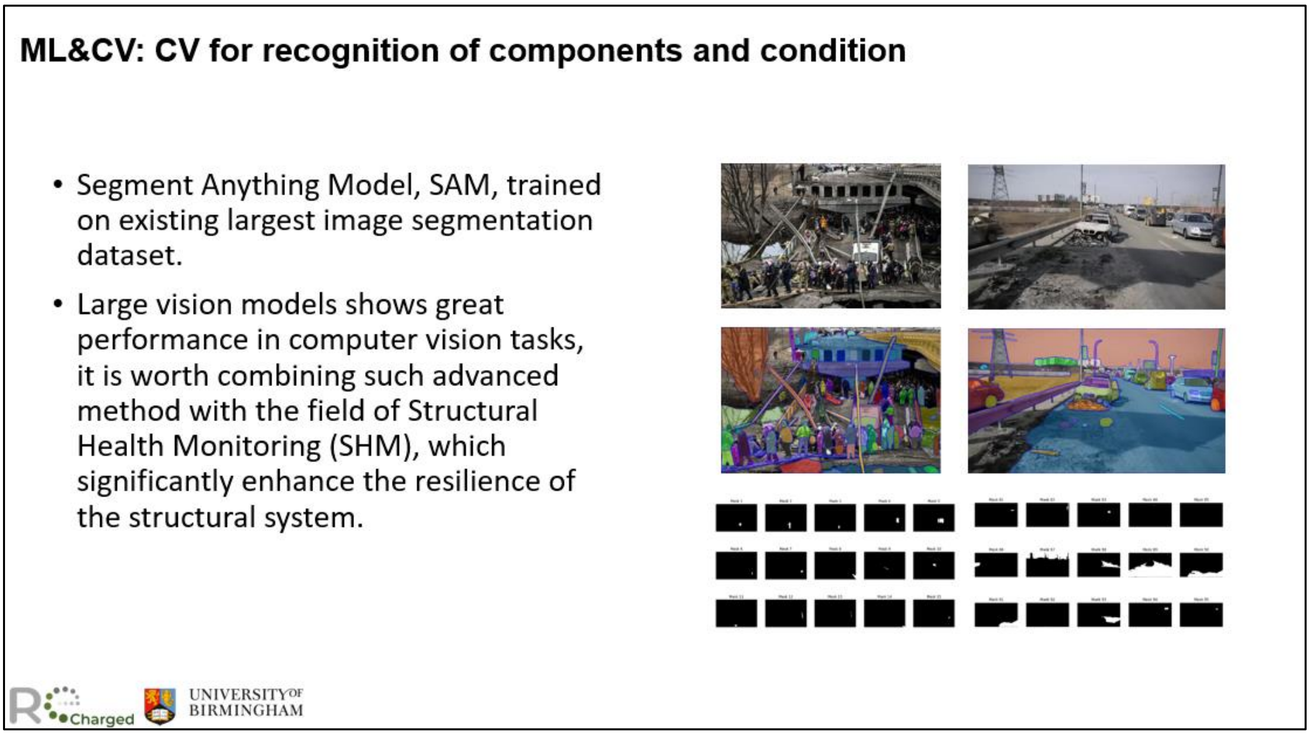
Defect classification involves various computer vision tasks to accurately identify and categorize structural issues. Image classification assigns labels to entire images based on observed defects. Object detection locates and identifies specific defect areas within images. Meta-learning enhances defect classification by enabling models to learn and adapt from a variety of defect types and scenarios. These tasks collectively improve the precision and efficiency of detecting and classifying defects in infrastructure.



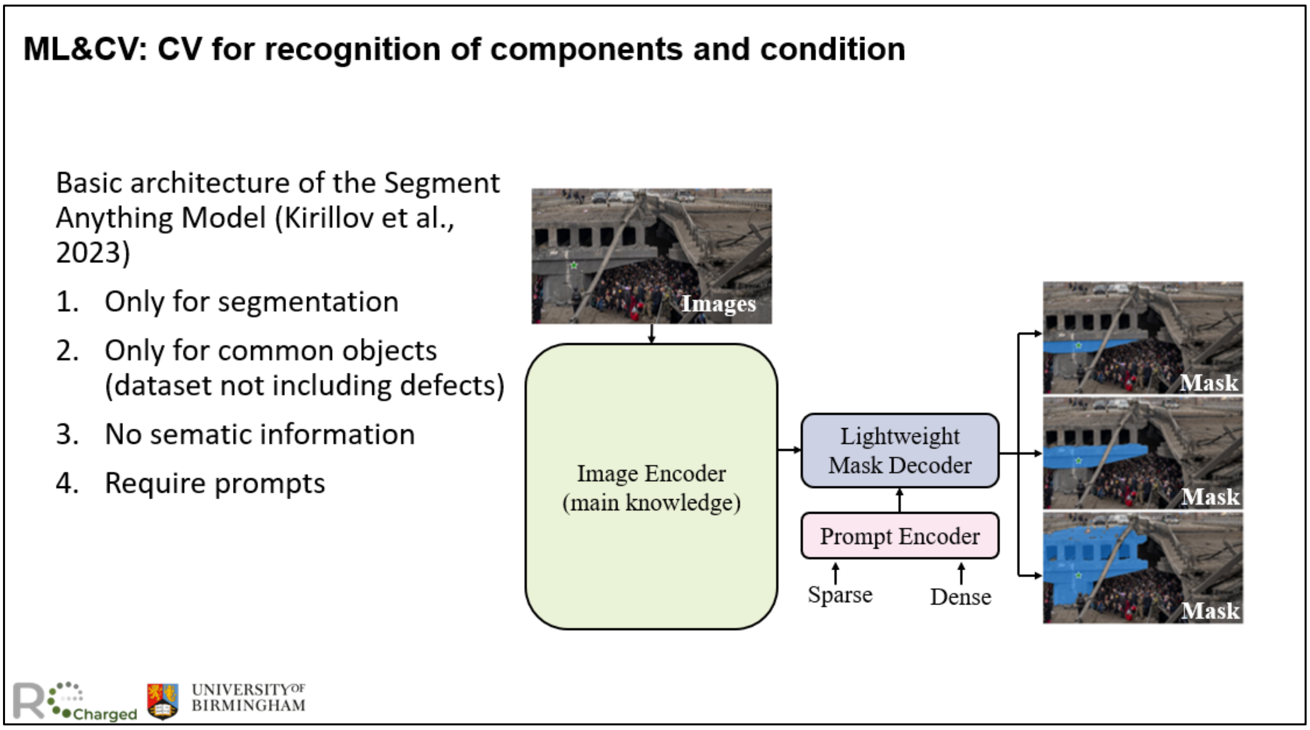
Semantic segmentation is a sophisticated computer vision task that surpasses image classification and object detection in complexity. It involves classifying each pixel in an image into one of a predefined set of classes, resulting in a segmented image where every segment is labeled accordingly. This detailed pixel-level classification is particularly valuable in damage detection, as it allows for precise delineation of both the location and shape of structural damage. By segmenting images at such a granular level, semantic segmentation enables accurate and comprehensive analysis, facilitating effective identification and assessment of damage in various infrastructure components.



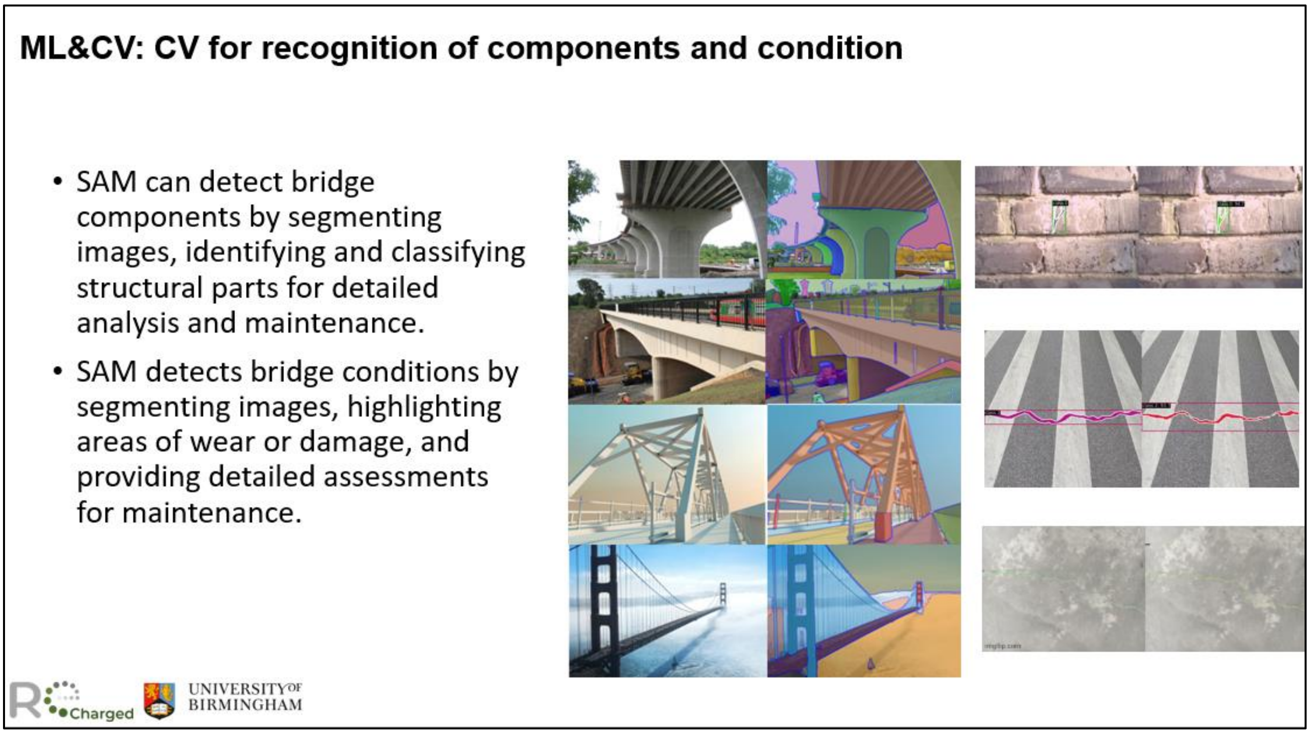
Machine learning can also be utilized for component recognition, specifically for identifying structural components. Structural component recognition involves detecting, localizing, and classifying characteristic parts of structures. In the image below, the original image is shown alongside segmented components, each of which has been architected. It is anticipated that the development of building blocks for autonomous navigation and data collection algorithms for robotic platforms will occur in the future. This development will likely incorporate heuristic methods. Additionally, learning-based recognition can be applied to 3D point cloud data, enhancing the accuracy and efficiency of structural component recognition.



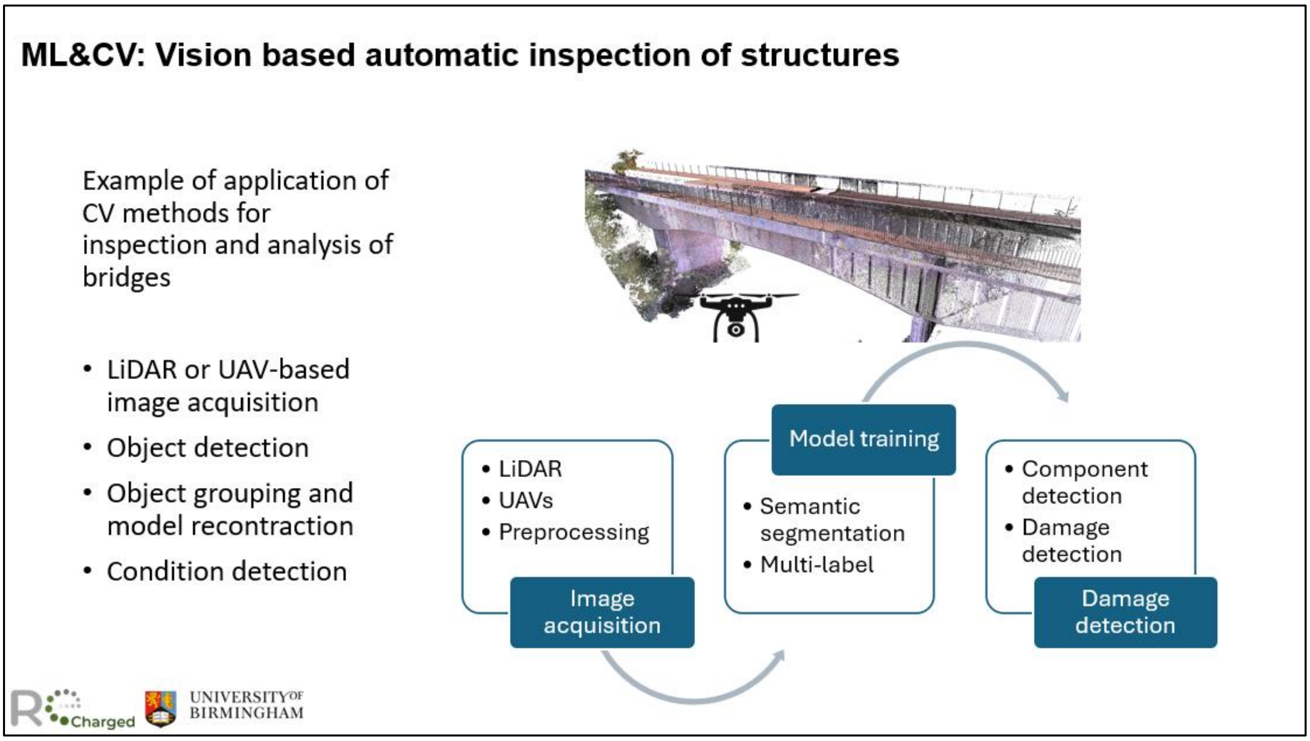
ChatGPT, a typical example of a large language model trained on extensive datasets with a vast number of parameters. Similarly, a large vision model operates on the same principle but is designed for image-related tasks. Today, we introduce a typical representative of a large vision model: the Segment Anything Model (SAM). SAM (Kirillov et al., 2023) is trained on the largest existing image segmentation dataset. When a user provides the model with any unseen image along with a prompt, such as a moving point, the required mask can be generated clearly and immediately.
Large vision models demonstrate exceptional performance in various computer vision tasks. It is worth integrating these advanced methods into the field of Structural Health Monitoring (SHM) to significantly enhance the resilience of structural systems.



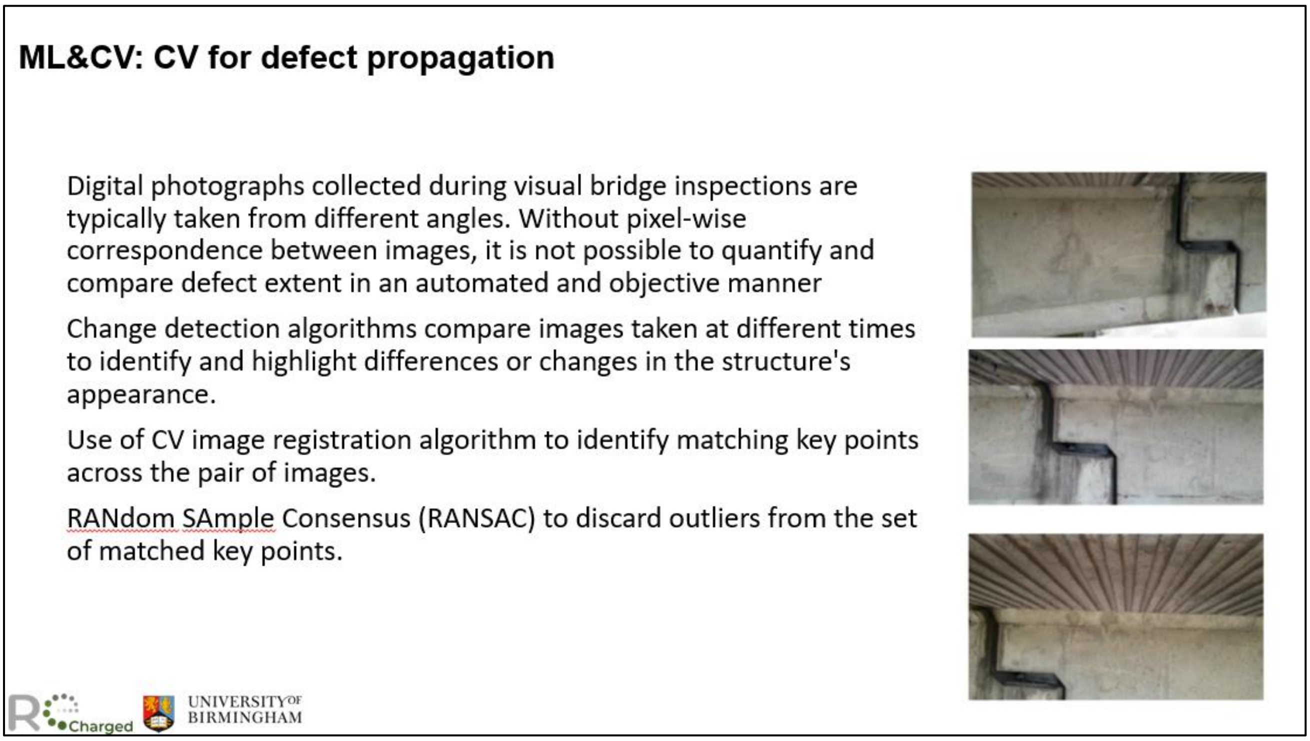
Traditional visual inspections of structural surface defects are labour-intensive, time-consuming, and subjective. Therefore, automation is crucial for increasing productivity. Basic architecture of SAM (Kirillov et al., 2023) is here; however, SAM can only do segmentation and only for common objects not for our tasks, no sematic information, and requires prompt to let model carry out. So, our aim is to propose an automatically framework for structural surface defect detection based on SAM.



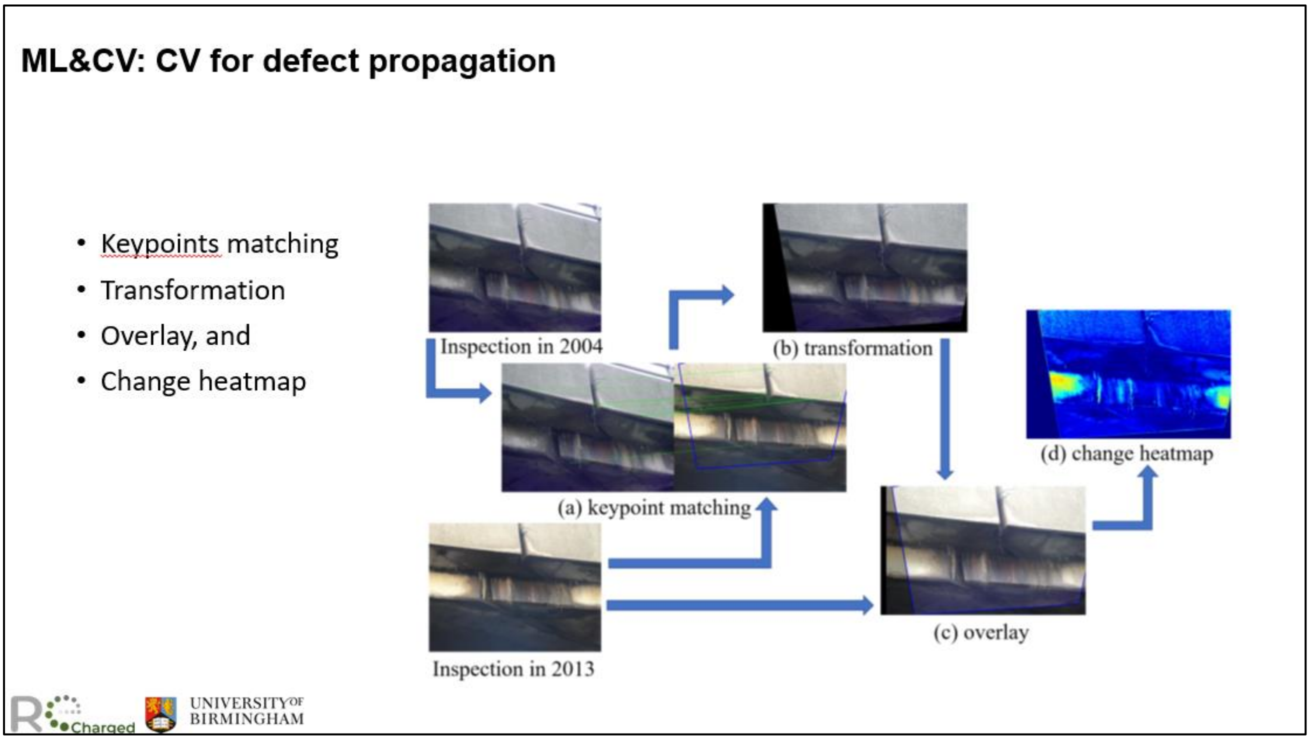
SAMcan detect bridge components by segmenting images into distinct regions, identifying and classifying parts like beams, joints, and cables. This enables precise analysis and monitoring of bridge infrastructure through detailed, component-level segmentation.
SAM can be utilized for bridge condition detection by segmenting images to identify and classify components (Ye, Z at al., 2024). It then analyzes these segments to assess the condition of each part, detecting any damage or deterioration for accurate and efficient maintenance planning



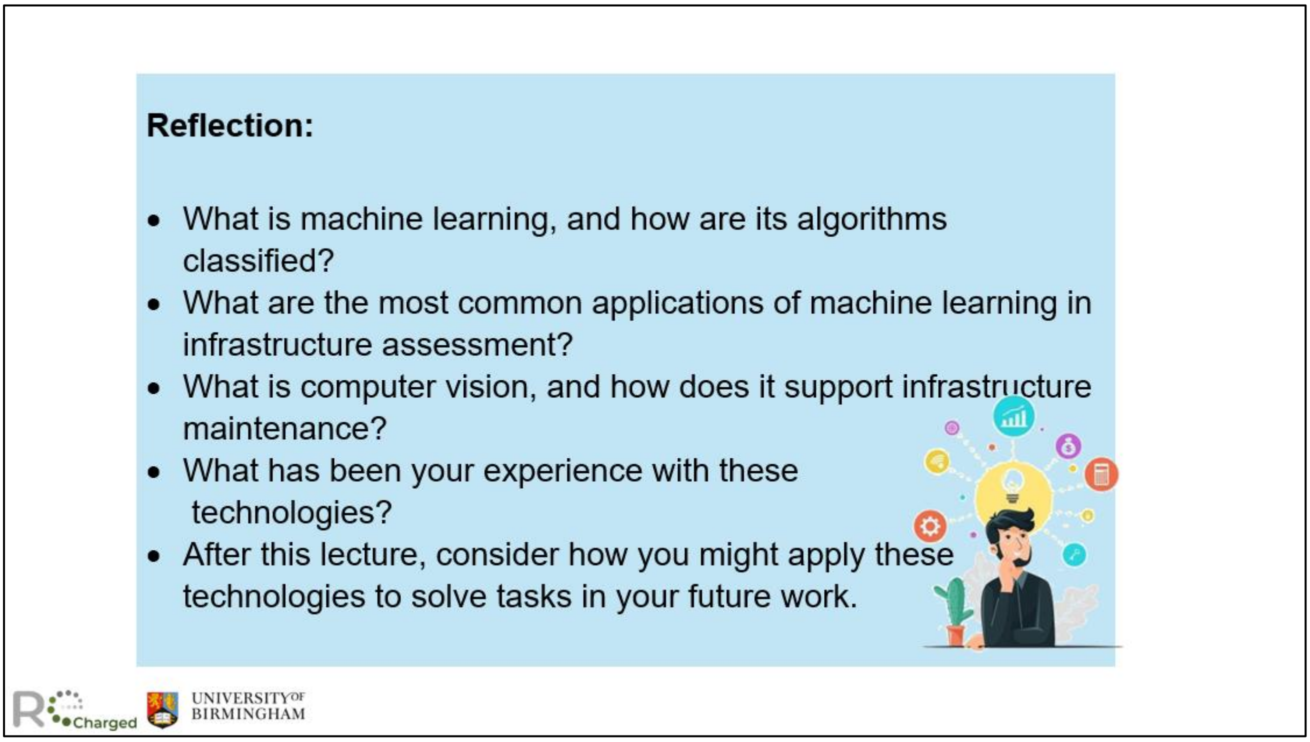
CV methods are increasingly applied to inspection and analysis, leveraging advanced technologies for comprehensive evaluations. LiDAR or UAV-based image acquisition captures high-resolution data of structures, providing detailed visual and spatial information. Object detection algorithms identify and locate key bridge components, such as beams and joints, within the acquired images. Object grouping and model reconstruction techniques then aggregate these detected components to create accurate 3D models of the bridge. Finally, condition detection analyzes these models to assess the structural health and identify defects or wear, enabling timely maintenance and ensuring safety.



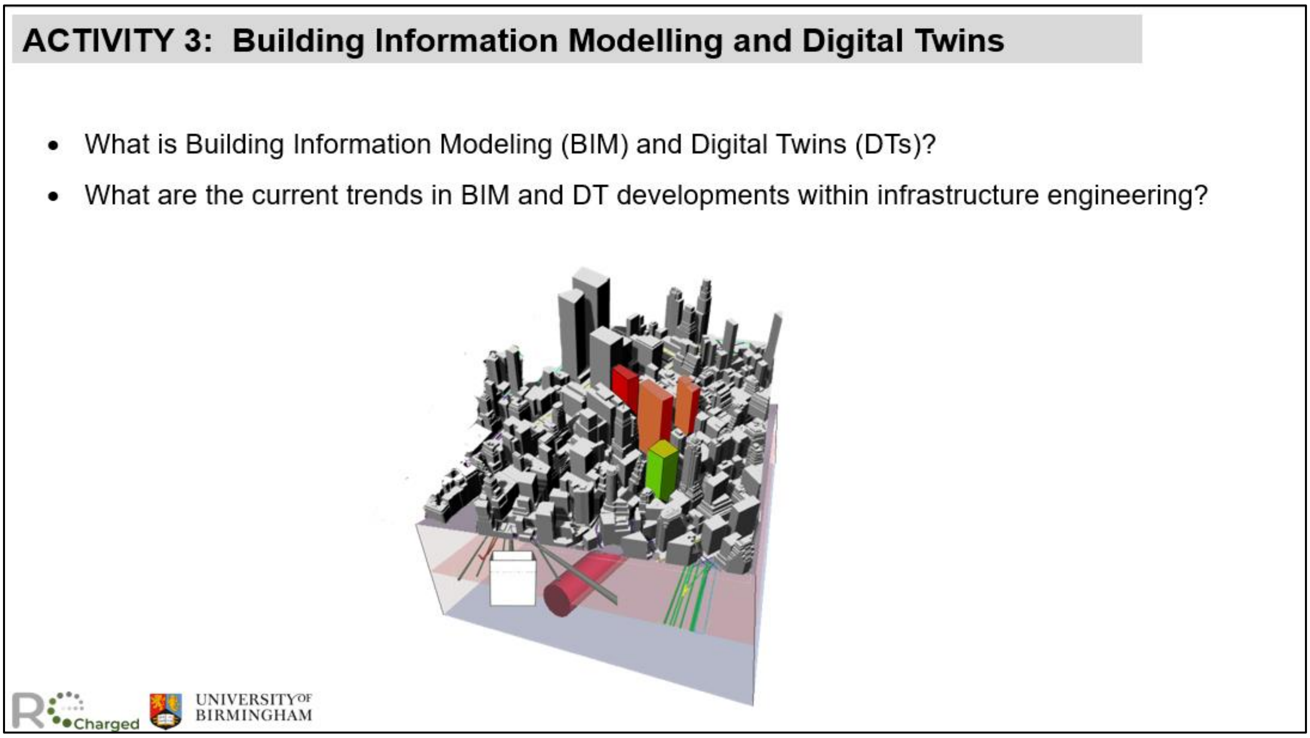
Digital photographs from visual bridge inspections are often captured from various angles, making it challenging to quantify and compare defects without pixel-wise correspondence between images. Change detection algorithms address this issue by comparing images taken at different times to highlight structural changes or defects. CV image registration algorithms are employed to identify matching key points across image pairs (Bush et al., 2022), ensuring accurate alignment. RANdom SAmple Consensus (RANSAC) is then used to filter outliers from these matched key points, enhancing the reliability of the change detection process. This combination of techniques enables automated, objective analysis of bridge condition over time.



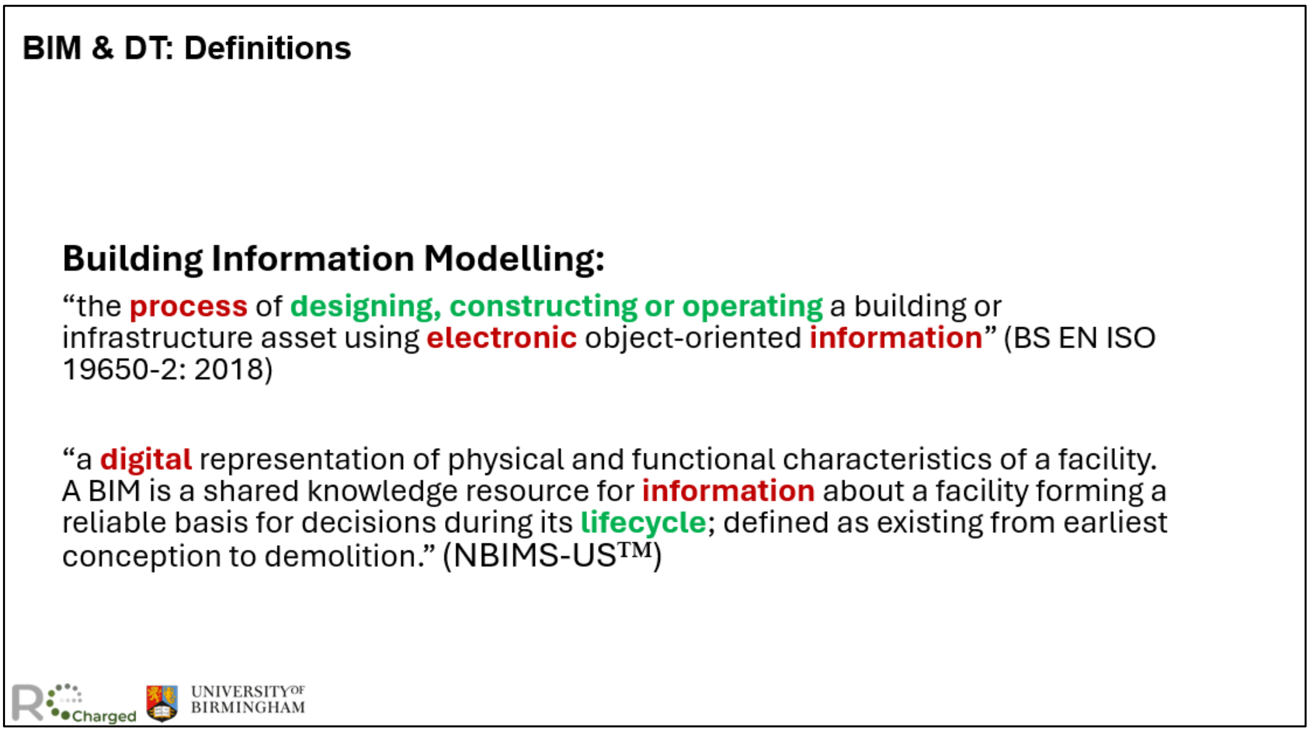
This helps in monitoring the progression of defects or damages over time (Bush et al., 2022). Tracking defect propagation involves several steps: key point matching aligns features across images, transformation adjusts for perspective changes, and overlay superimposes images to compare defect locations. Change heatmaps visualize and quantify defect growth, highlighting areas of increased damage over time for effective monitoring and analysis.



Activity 3: Building information modelling and Digital Twins



The aim of this lecture is to learn about fundamentals of Building Information Modelling (BIM) and its application for digital modelling of infrastructure. We will also discuss different between BIM and digital twins and how BIM could evolve to digital twin.



Building Information Modelling (BIM) is defined in two key ways. According to BS EN ISO 19650-2: 2018, BIM is "the process of designing, constructing, or operating a building or infrastructure asset using electronic object-oriented information." This definition emphasizes BIM's role in managing and utilizing digital data throughout the asset's lifecycle.

Alternatively, the NBIMS-US™ describes BIM as "a digital representation of physical and functional characteristics of a facility." This definition highlights BIM as a shared knowledge resource that provides a reliable basis for decision-making from the earliest conception through to demolition. Both definitions underscore BIM's integral role in comprehensive facility management. *(BS EN ISO 19650-2: 2018)*

BIM & DT: Definitions

- **Building** is the verb '*to build*' rather than the noun 'a building'.

It is therefore relevant to any asset of the built environment (e.g. tunnel, a road).

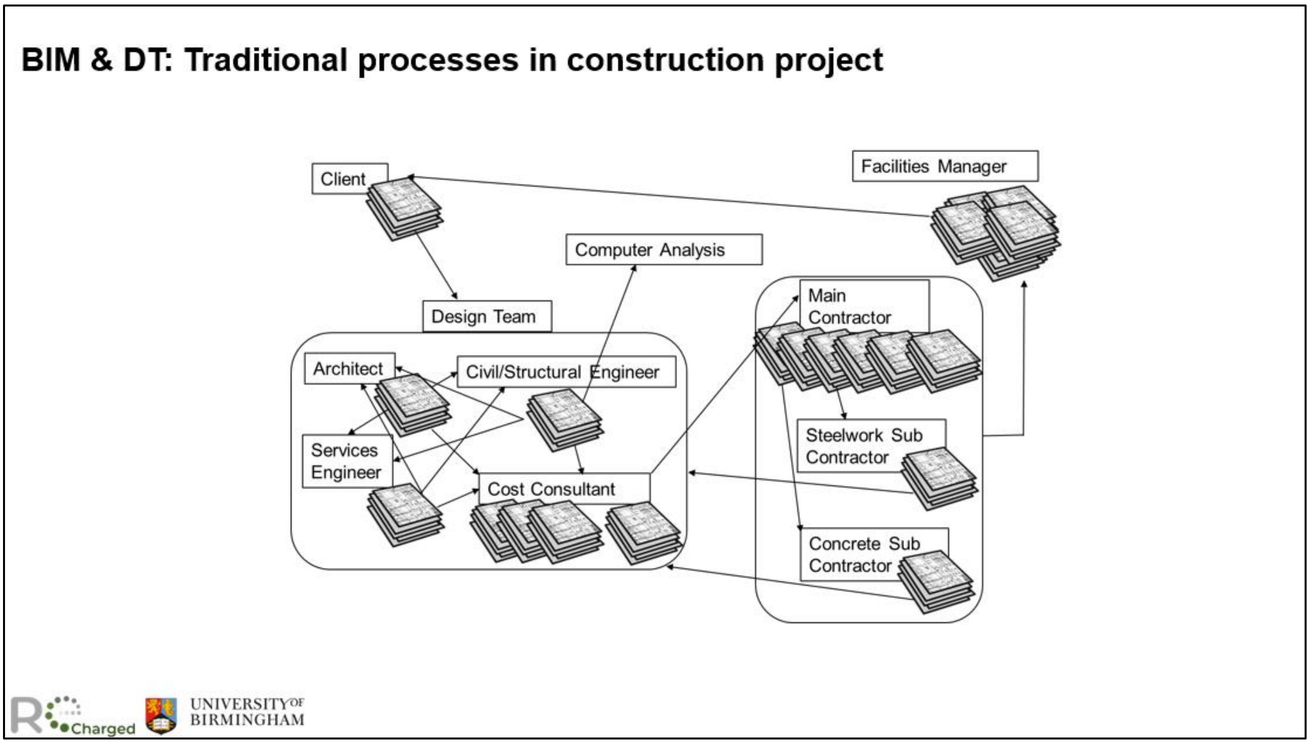
- **Information** (or more specifically 'the sharing of structured information') is the fundamental concept of BIM.

This includes both *geometric* and *non-geometric information* (such as time, cost, fire-rating etc.).

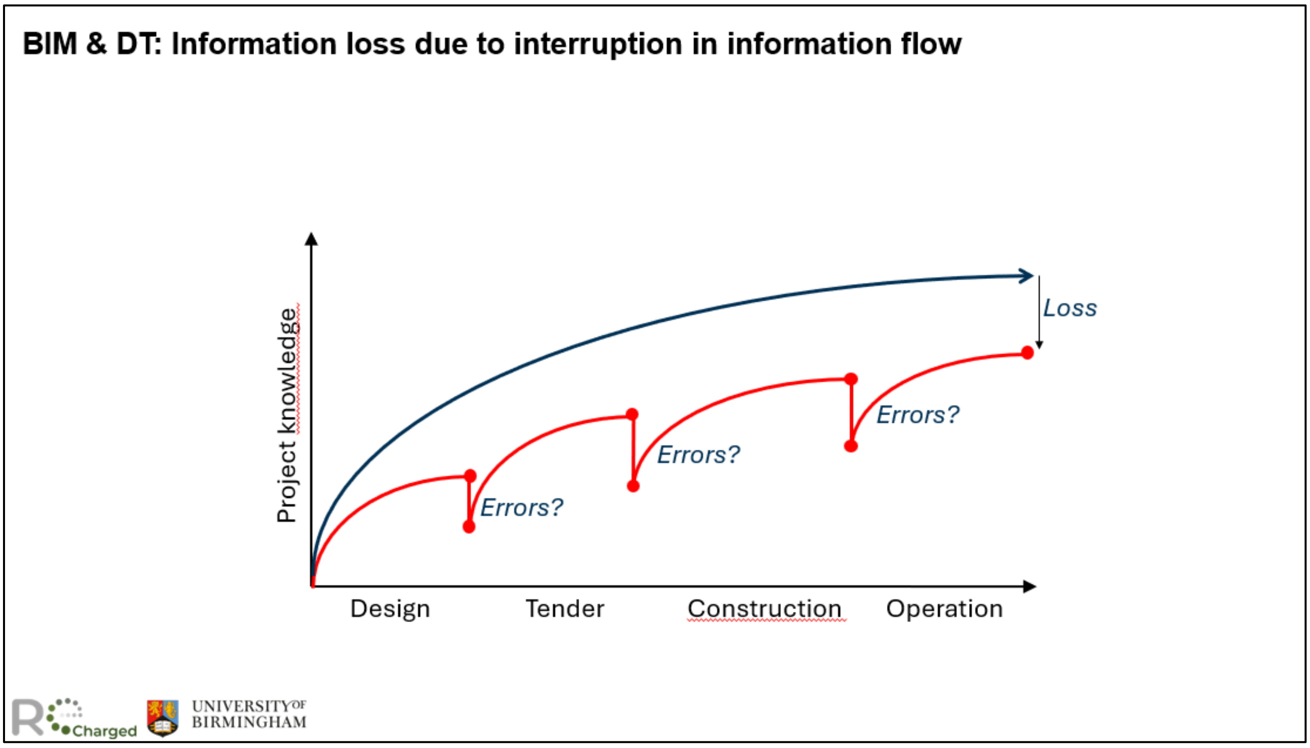
- **Modelling** refers to the '*representation of a system or process*' rather than a '3-dimensional representation of a person or thing'.

Though there can be no doubt that geometric representation is important, we must be able to simulate the various facets of the design of an asset (structural, architectural, building services etc.), the construction of the asset, and the operation of the asset.

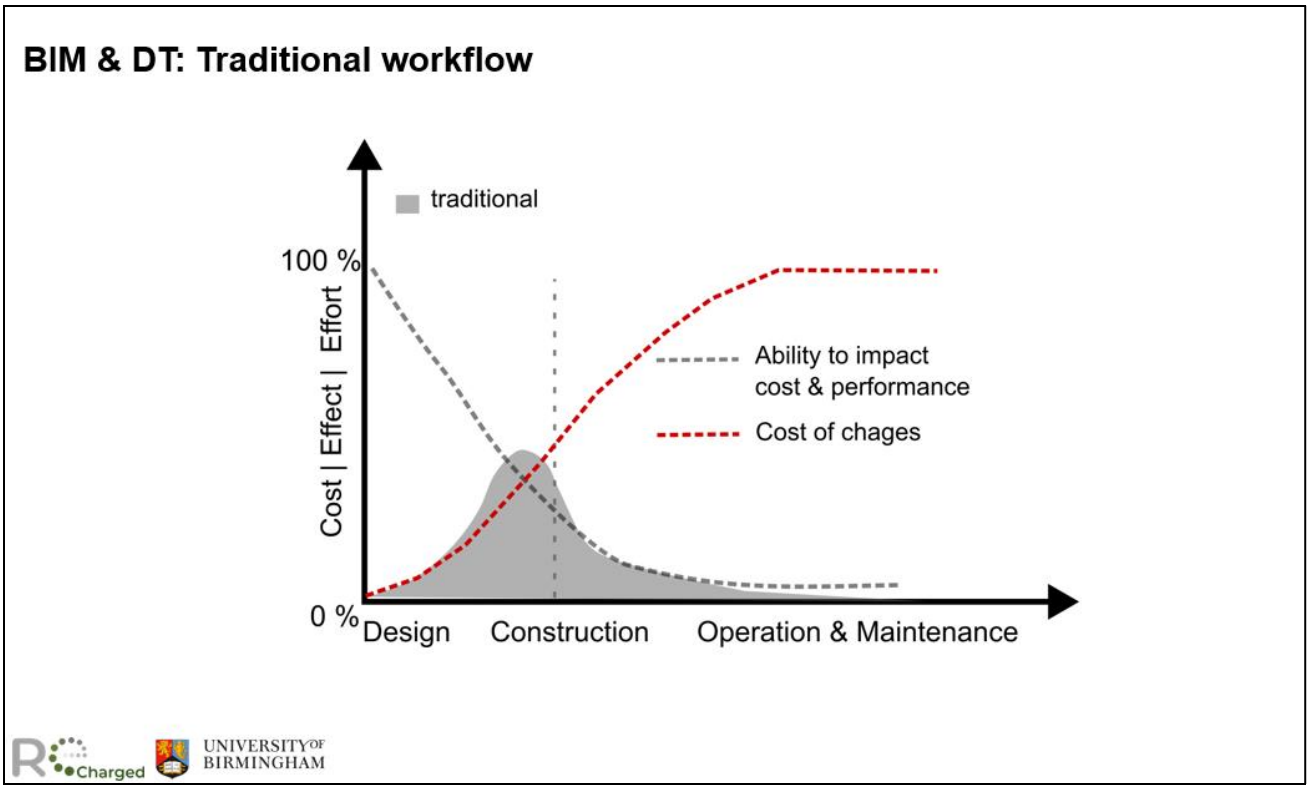
Building Information Modelling (BIM) encompasses more than just the creation of digital models of physical structures; it fundamentally involves the verb "to build," applying to a process of continuously building models and all assets in the built environment, such as tunnels and roads, not just buildings. "Information" in BIM emphasizes the sharing of structured data, including both geometric aspects and non-geometric details like time, cost, and fire ratings. This broadens BIM's scope beyond mere 3D visualization. "Modelling" in BIM refers to the comprehensive representation of systems or processes, rather than just creating 3D models of objects. While geometric representation is crucial, BIM's true value lies in its ability to simulate various design facets—structural, architectural, and building services—alongside the construction and operational phases of an asset. This holistic approach ensures detailed, accurate, and useful simulations throughout the asset's lifecycle.



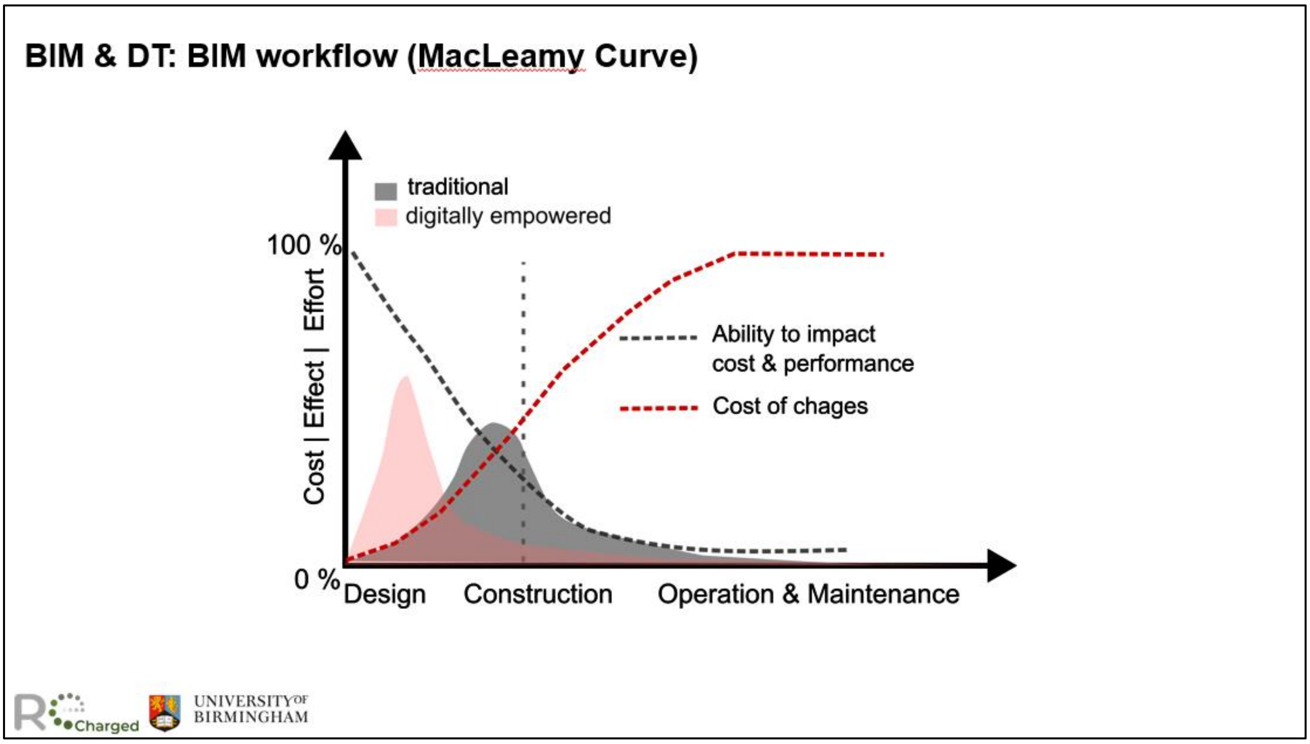
Traditional construction project information exchange relies on physical documents, such as blueprints and reports, and face-to-face meetings. Information is often communicated through hard copies, faxes, and emails, leading to potential delays and inefficiencies. Coordination among stakeholders can be fragmented, impacting project accuracy and timelines.



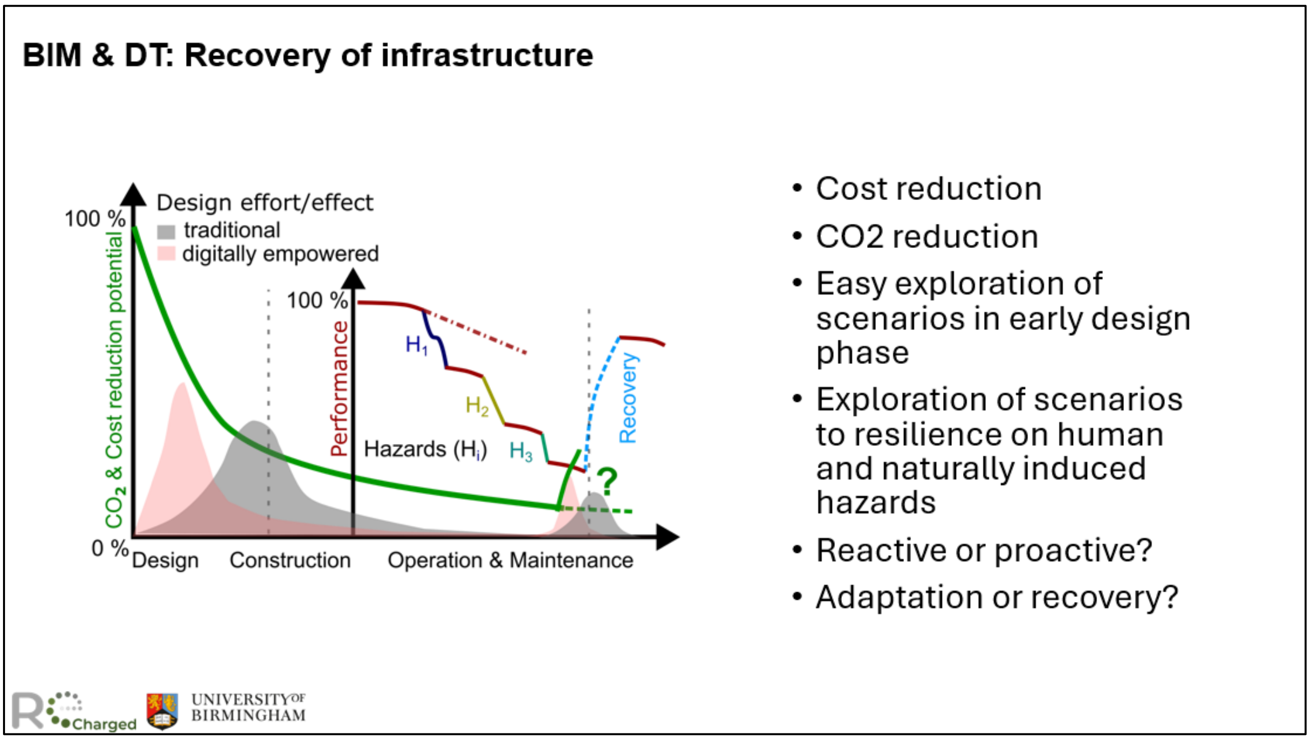
Information loss in construction projects occurs when in the transition between project phases and between stakeholders (Borrmann et al., 2018). Delays in communication, incomplete data transfer, or missed updates can lead to errors, misunderstandings, and inefficiencies. This loss hampers decision-making, coordination, and project progress, ultimately affecting quality, cost, and timelines.



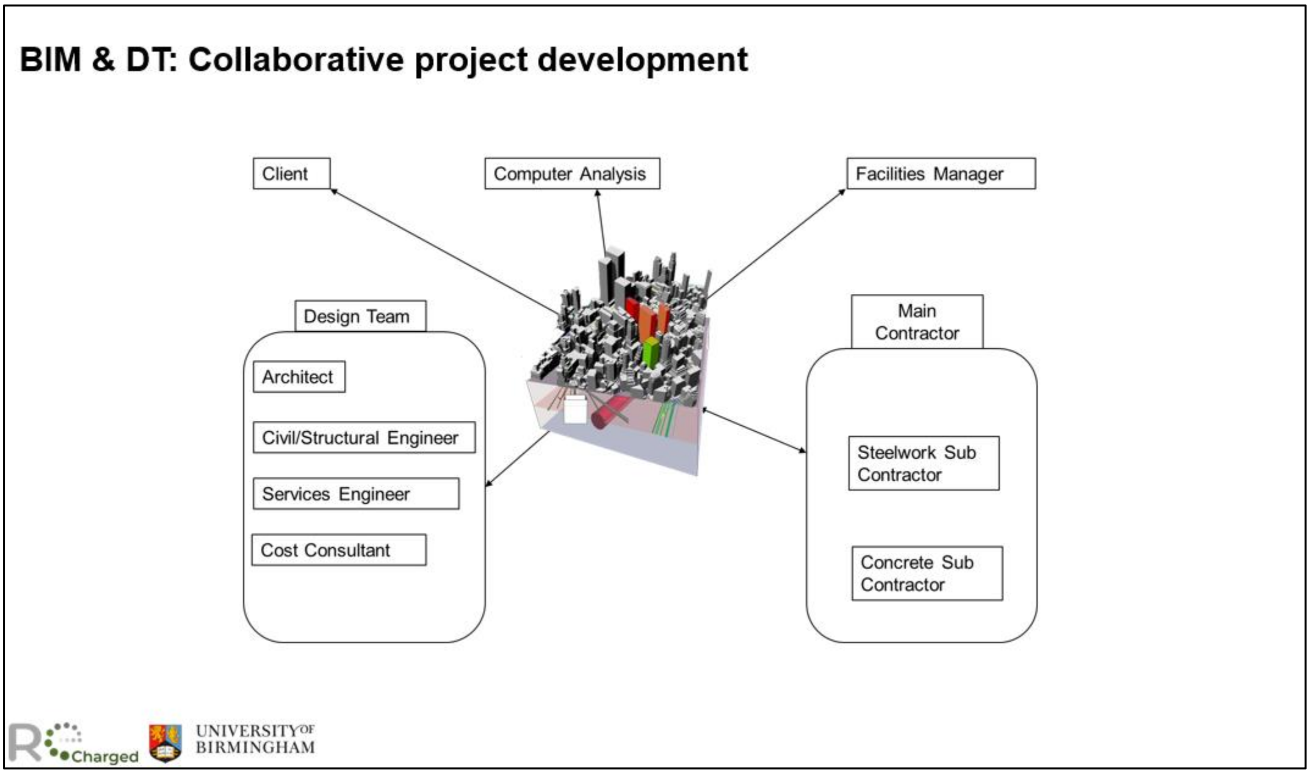
In the McLeamy Curve, traditional BIM workflows often start with limited information during early design stages, gradually improving as the project progresses. Initially, detailed design data is sparse, but as the project advances, data becomes richer and more accurate, enhancing decision-making and reducing errors during later stages.



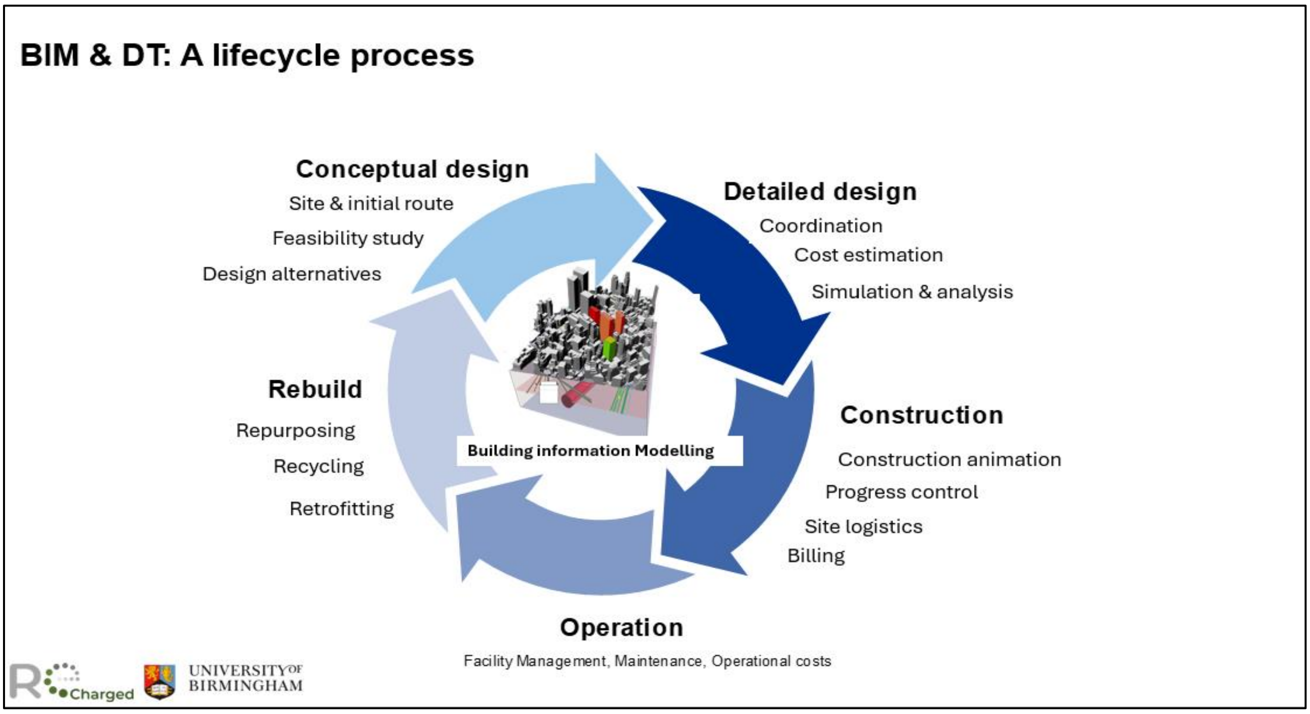
The McLeamy Curve illustrates how the value of design decisions and the cost of changes evolve throughout a project. In BIM workflows, early stages involve broad, less detailed models, leading to limited accuracy and higher flexibility. As the project progresses, BIM models become more detailed and accurate, improving decision-making and reducing the cost of changes. Initially, design changes are easier and cheaper to implement, but as the project advances, modifications become more costly and complex. By leveraging BIM's iterative capabilities, teams can make informed decisions early on, ultimately enhancing efficiency and reducing overall project costs.



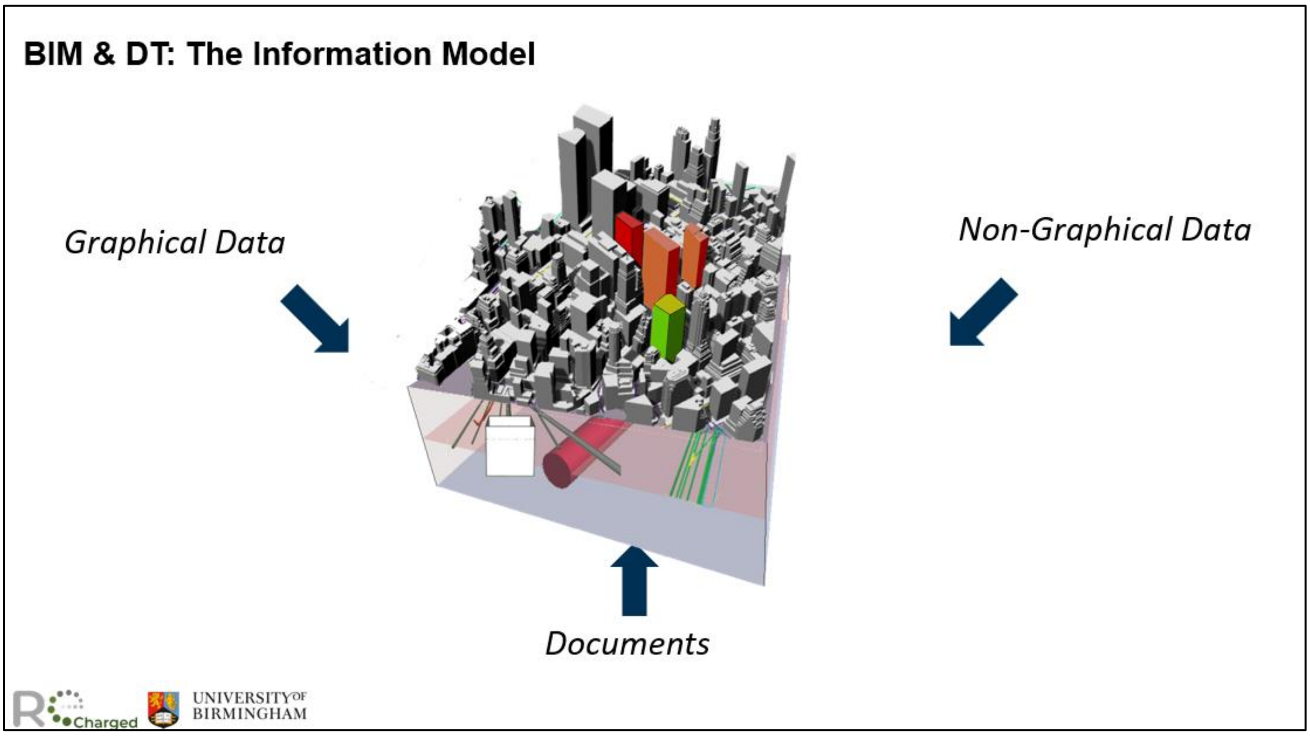
BIM offers several key benefits. Cost reduction is achieved through improved accuracy in planning and resource management, minimizing unexpected expenses. CO2 reduction results from optimized designs that enhance energy efficiency and reduce waste. BIM facilitates easy exploration of scenarios during the early design phase, enabling the evaluation of different design options. It also supports exploration of resilience scenarios to assess responses to human or natural hazards, aiding in both reactive and proactive strategies. This capability enhances adaptation and recovery, ensuring that structures can be better prepared for and recover from potential disruptions.



In BIM collaborative project development, BIM serves as a central repository for all project data, fostering seamless teamwork among stakeholders. This centralized model integrates information from various disciplines—architectural, structural, and MEP—into a single digital platform. By consolidating data, BIM ensures that every team member has access to up-to-date, accurate information, promoting efficient communication and coordination. This collaborative approach enables real-time updates, reduces conflicts, and enhances decision-making throughout the project lifecycle. It facilitates shared understanding, streamlined workflows, and better management of project changes, ultimately leading to improved project outcomes and more effective problem-solving.



BIM enhances lifecycle processes by providing a comprehensive digital representation of a building or infrastructure asset throughout its entire lifespan (Borrmann et al., 2018). From initial design to construction, operation, maintenance, and eventual demolition, BIM integrates and manages all relevant data in a single model. This continuous access to up-to-date information supports efficient planning and coordination, reduces errors, and optimizes resource use. During operation and maintenance, BIM aids in tracking asset performance, scheduling repairs, and managing renovations. By facilitating data-driven decision-making and streamlining workflows, BIM ensures that the asset's lifecycle is managed effectively, leading to improved performance and cost savings.



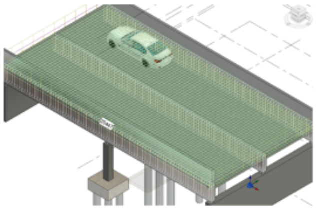
A BIM model integrates graphical data (3D visual representations of building elements), non-graphical data (attributes like material properties, costs, and performance metrics), and documents (such as drawings, specifications, and reports). This comprehensive combination provides a holistic view of the asset for effective management and analysis.

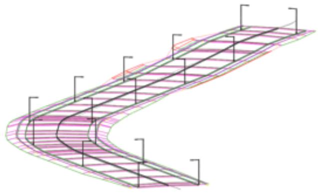
BIM & DT: The Information Model

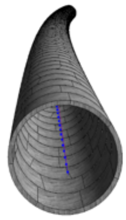
1. Graphical Data

Geometric modelling

- *What shape does an infrastructure component have?*
- *What volume, surface area is associated with it?*
- *Does it collide with other components?*







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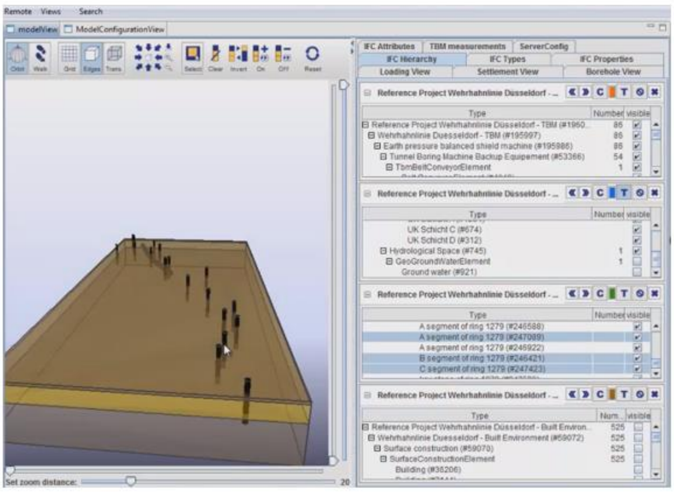
Graphical Data in BIM involves geometric modeling to define the shape of infrastructure components. This includes determining their volume, surface area, and spatial relationships. It answers questions about the component's dimensions and whether it interacts or collides with other elements within the model. This graphical representation ensures precise design and spatial coordination throughout the project.

BIM & DT: The Information Model

2. Non-Graphical Data

Semantic modelling

- *What is the type of the component?*
- *What are its properties, such as material?*
- *What are its relations to other components?*



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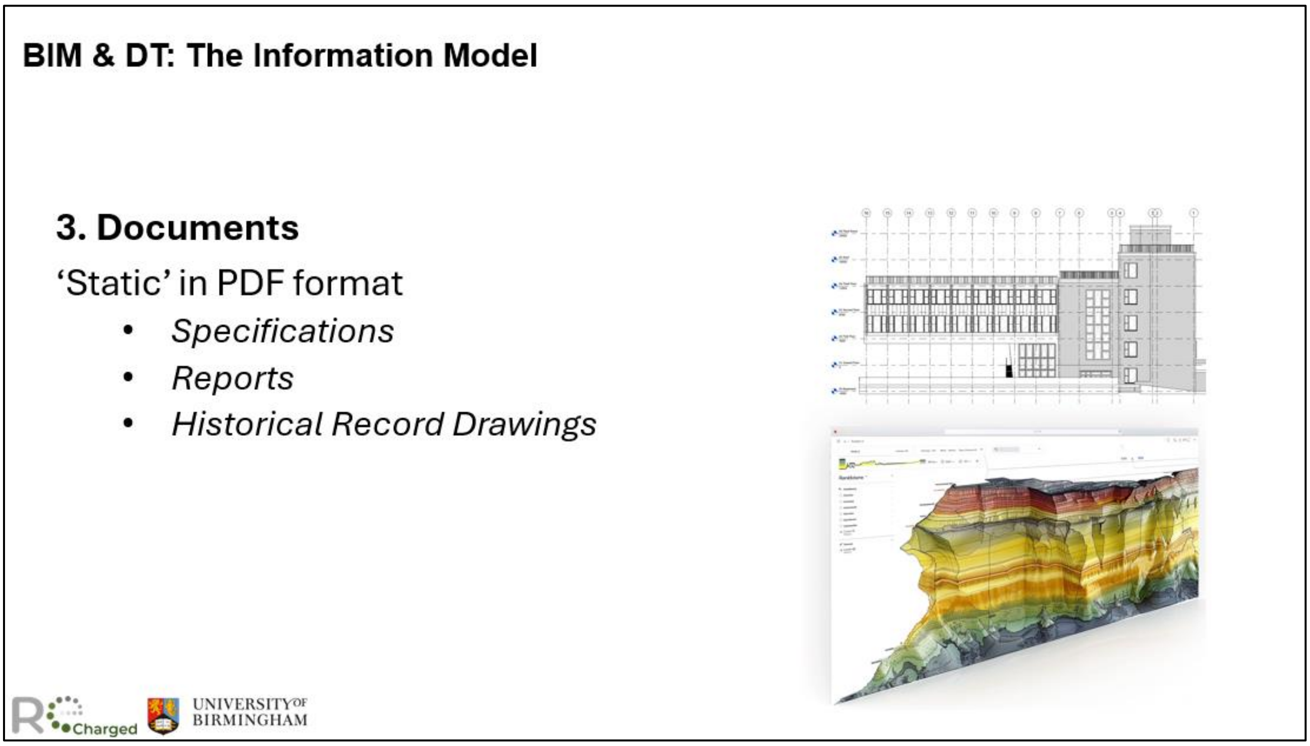
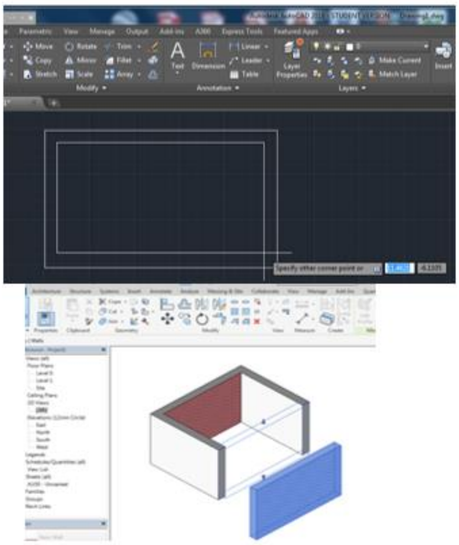
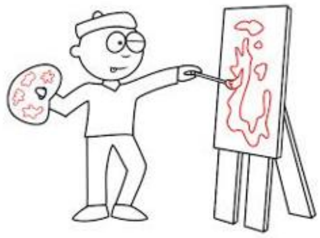
Non-Graphical Data in BIM (Koch et al., 2017) focuses on semantic modeling, which involves defining the type of each component and its properties, such as material. It also examines the relationships between components, detailing how they interact or connect with one another. This data provides essential context and functionality beyond the visual aspects, ensuring a comprehensive understanding of the asset's characteristics and their implications for design and operation.



Documents in BIM encompass essential static information, typically provided in PDF format. This includes specifications outlining detailed requirements, reports summarizing project findings or progress, and historical record drawings capturing the as-built conditions and modifications over time. These documents complement the dynamic BIM model, offering critical insights and records that support comprehensive project management and historical reference throughout the asset's lifecycle.

BIM & DT: Producing an Information Model





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CAD (Computer-Aided Design) and BIM serve distinct purposes in design and construction. CAD focuses on creating detailed 2D drawings and 3D models, often representing individual components without integrating their context or relationships. It's akin to drafting or "paining" precise architectural plans. In contrast, BIM is like building with LEGO blocks, where each component is a detailed, intelligent object with embedded information about its properties, functions, and relationships. BIM integrates all project data into a unified model, facilitating collaboration, visualization, and lifecycle management. While CAD excels in detailed drawing, BIM enhances coordination and efficiency across the entire project.

BIM & DT: BIM Objects

A BIM object is a combination of many things:

- **Geometry** representing the objects physical characteristics
- Material **properties** such as stiffness, density, cohesion
- **Visualisation data** giving the object a recognisable appearance
- **Functional data** such as detection zones that enables the object to be positioned correctly

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A BIM object is a multifaceted entity encompassing various types of information. It includes geometry, which defines the object's physical shape and dimensions. Material properties, such as stiffness, density, and cohesion, detail the object's physical attributes and behavior. Visualization data provides a realistic appearance, making the object easily recognizable within the model. Additionally, functional data, like detection zones, ensures the object is positioned and operates correctly within the overall system. This comprehensive integration of data allows BIM objects to serve as intelligent components within a unified digital model, enhancing both design accuracy and operational efficiency.

BIM & DT: Object-Based Parametric Modelling:

Each object class has parameters (variables)

In parametric design the designer defines **instances** of objects within the model.

The **parameters** (or variables) which position object instances include distance, angles, and rules like 'attached to', 'parallel to' or 'distance from'

On parameter change → **automatic update** of dependent parameters

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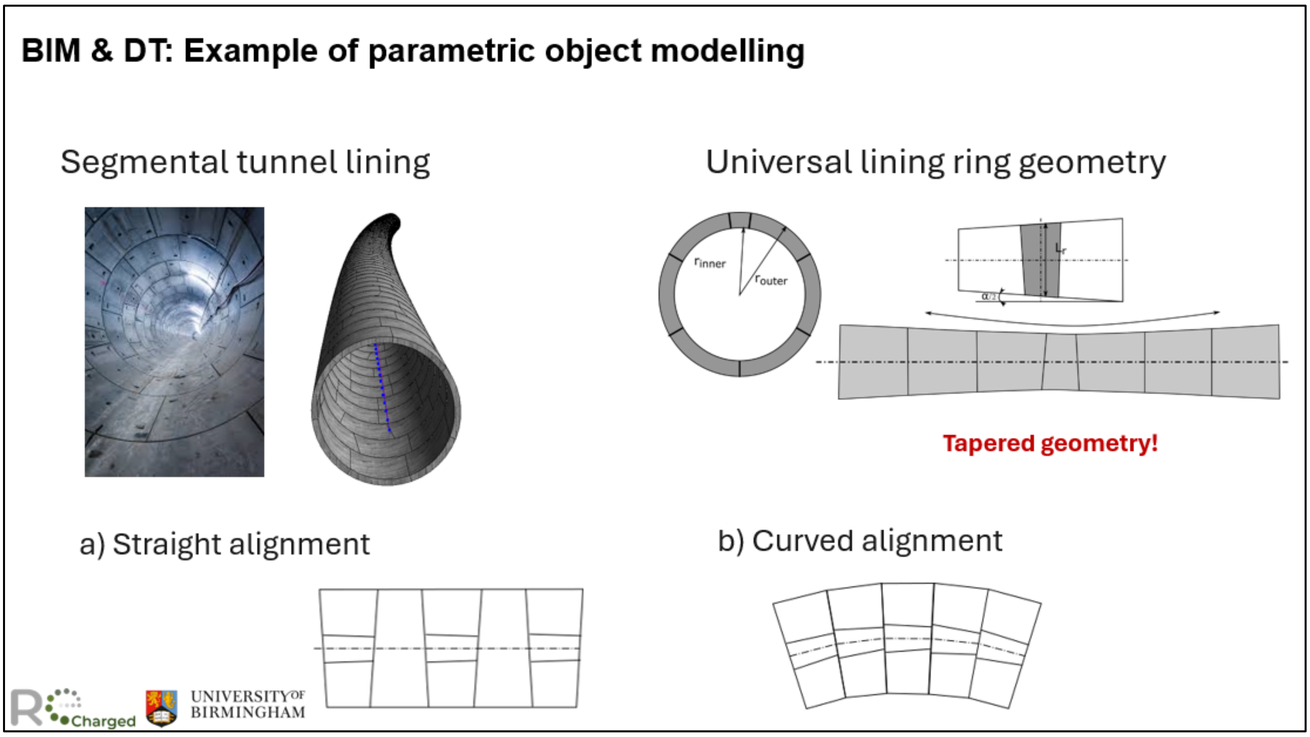
In parametric design, each object class in a BIM model is defined by parameters or variables, such as distance, angles, and relational rules like ‘attached to’ or ‘parallel to’. Designers create instances of objects within the model by specifying these parameters. When a parameter changes, the model automatically updates all dependent parameters, ensuring consistency and accuracy throughout the design. This dynamic approach streamlines modifications and enhances the overall efficiency of the design process.



The lining segments are precast elements that are installed through an erector during the standstill of the TBM in a lining ring to ensure the tunnel stability behind the shield (Ninic et al., 2020b). The geometry of the entire ring and its individual segments as well as the arrangement of the joints must be designed such that the can be easily moulded. In order to enable a modular segment production, the solution is to employ so-called universal rings. Tapered geometry of the universal ring and main geometrical parameters. (b) Alignment of subsequent rings is determined by means of rotation angle. In BIM we can create libraries of classes of these elements. These components will be fully parametric. Then we can implement algorithms to automatically import objects (instances of the class) with assign parameters and establish intelligent relationships between objects to carte rings in a way that they are perfectly aligned to any arbitrary tunnel trace.

BIM & DT: What is BIM not?

- Models that contain 3D data only and no (or few) object attributes
- Models with no support of behavior (models that cannot adjust when changes are added because they do not use parametric modelling)
- Models that are composed of multiple 2D CAD reference files that must be combined to define the building
- Models that allow changes to dimensions in one view that are not automatically reflected in other views

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BIM is not simply a model with 3D data lacking detailed object attributes. It is not a static model without parametric capabilities, which means it cannot adjust to changes dynamically. BIM is also not a collection of separate 2D CAD files that need manual integration to define a building. Additionally, BIM does not involve models where changes to dimensions in one view are not automatically updated across all other views. Unlike these limitations, BIM integrates comprehensive data, supports dynamic adjustments through parametric modeling, and ensures consistency across different views and elements within the project.

BIM & DT: Lonely BIM vs Federated models

You could build a BIM model in software (e.g. Autodesk) on your own and generate 2D drawings from it.

Some companies do this. This Level 1 BIM, sometimes called 'LonelyBIM'.

Very useful way to analysis a building and generate drawings but not in the true spirit of BIM.

The real benefit is when all disciplines can produce a 'Federated Model', Level 2 BIM.

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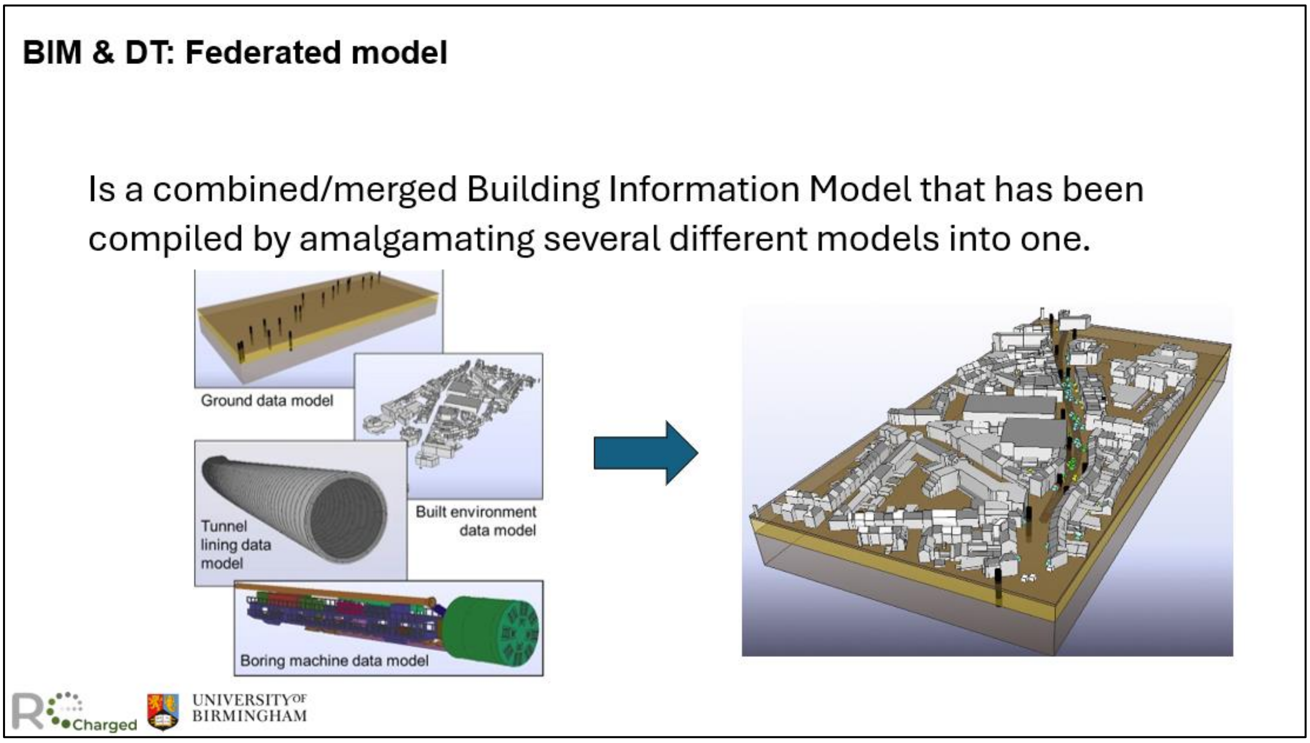
Building a BIM model independently using software like Autodesk and generating 2D drawings from it, often referred to as Level 1 BIM or 'LonelyBIM', offers valuable insights for analyzing a building. However, this approach does not fully embrace the collaborative essence of BIM. Level 2 BIM, or 'Federated Model', represents the true spirit of BIM. It involves integrating models from various disciplines into a single, comprehensive model, fostering collaboration and ensuring that all aspects of the project are synchronized. This federated approach enhances coordination, reduces conflicts, and maximizes the overall effectiveness and efficiency of the project.



The federated BIM model for tunneling is a digital assembly created by integrating federating components into a cohesive model (Koch et al., 2017). It combines the detailed City model, capturing surface geography and infrastructure; the Tunnel Lining model, depicting precise structural elements and material specifications; and the TBM (Tunnel Boring Machine) model, illustrating operational details and machinery layout. This merged Building Information Model enhances coordination, allowing for seamless visualization and analysis. By unifying these distinct models, engineers and planners can more effectively manage the tunneling project, ensuring that each element aligns perfectly within the broader urban context.

BIM & DT: What is Digital Twin?

- “a Digital Twin is an exact digital replica of a construction project or asset” (Wiki)
- But DTs are **virtual replicas** of real-world physical products or **systems**. DTs integrate data with 3D digital model representation, Machine Learning (ML), AI and Data Science to **create living transdisciplinary simulations that update and change in real-time** with changes of the physical counterpart **over the whole lifecycle.** They are then employed for optimising processes, supporting decision making, virtual control, and analysis.

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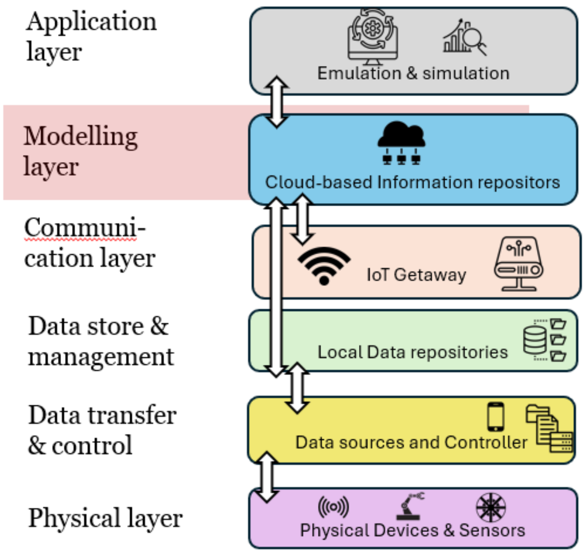
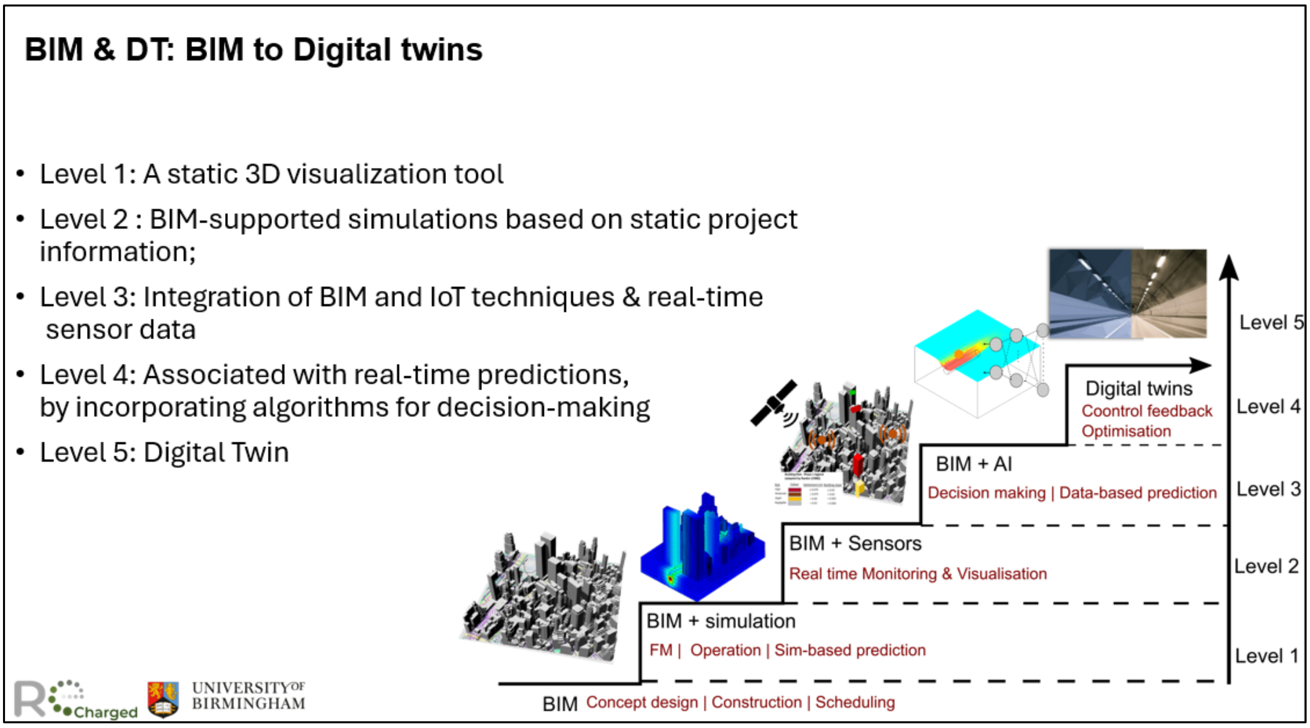
BIM and DTs

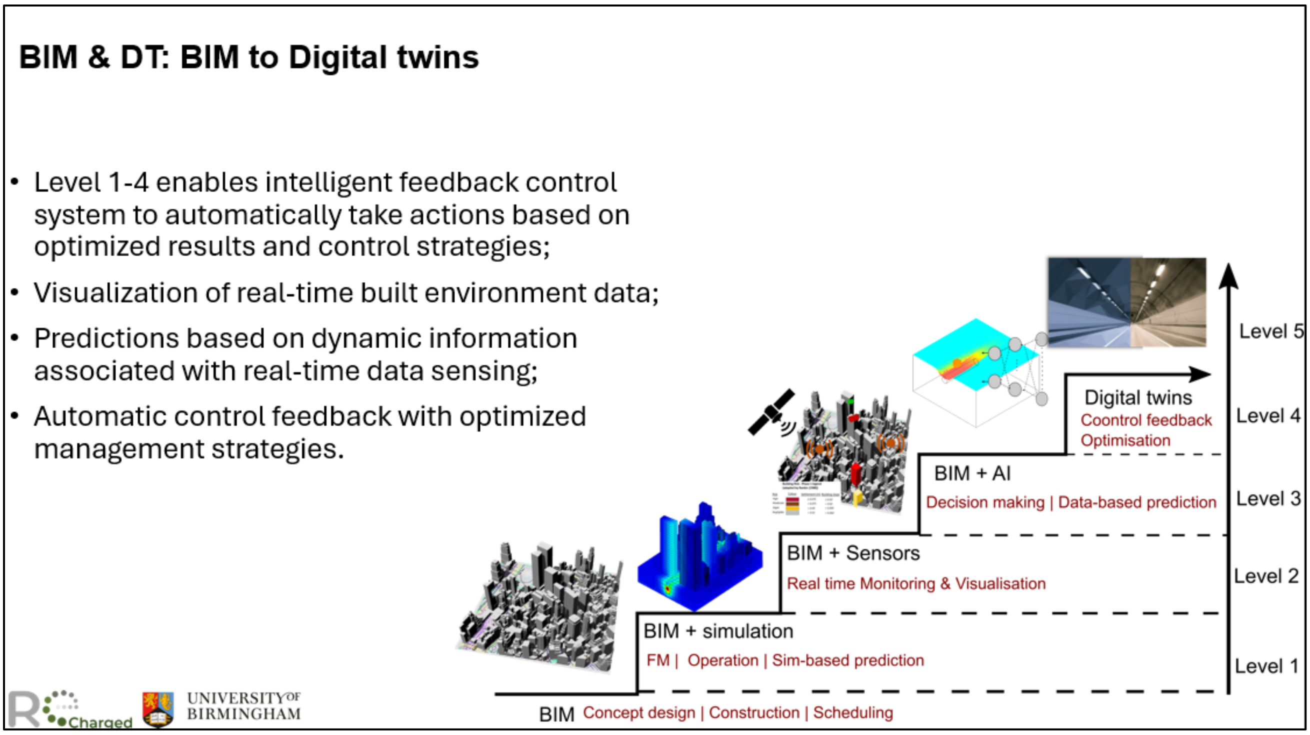
- In general DTs consist of:
  - Physical layer
  - Data transfer, store, management and communicating layer
  - Modelling layer
  - Application layer
- BIM can be
  - subset of DT (model)
  - Or a way to achieve DT



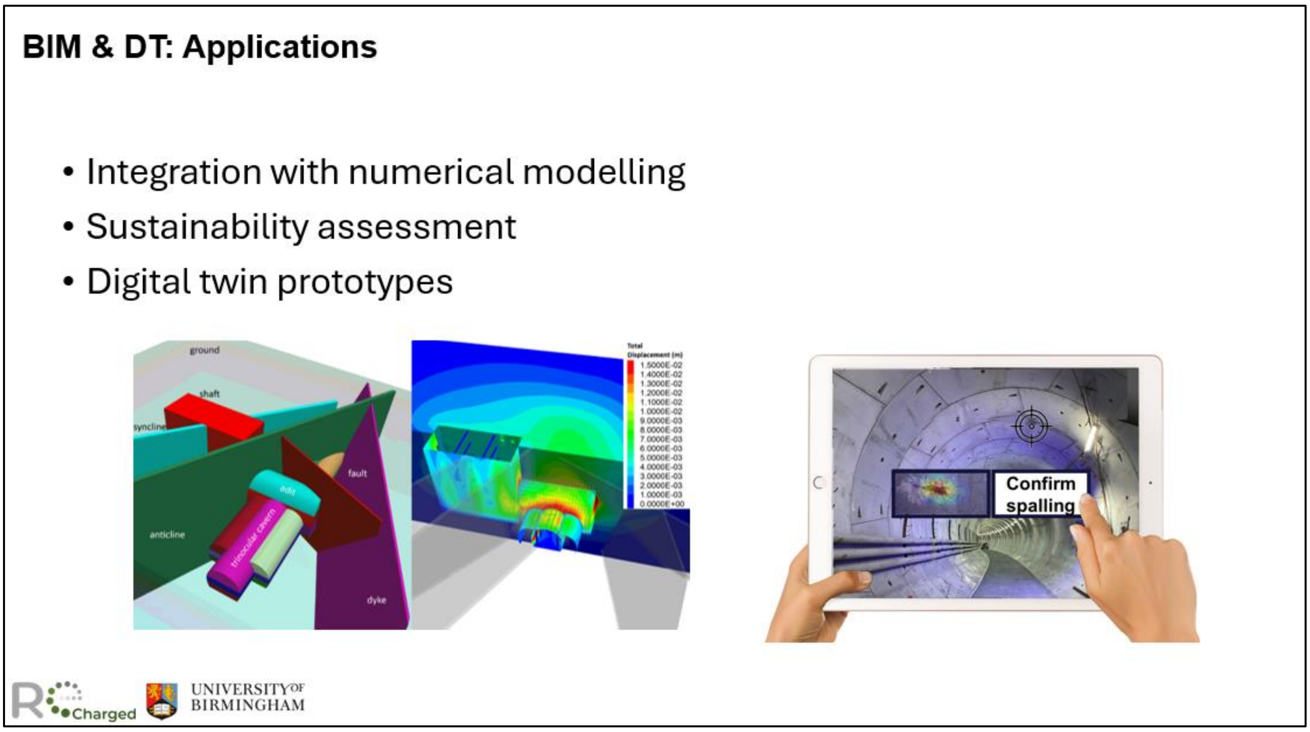
Digital Twins (DTs) are multi-layered systems encompassing several key components. The Physical Layer represents the real-world object or system, while the Data Transfer, Storage, and Management Layer handles the flow and organization of information. The Modelling Layer interprets and simulates the physical entity, and the Application Layer uses this data to drive insights and decision-making. Building Information Modeling (BIM) can function as either a subset of the DT, providing detailed models of structures, or as a method to achieve a Digital Twin by offering a dynamic, data-rich representation of the physical asset, enhancing real-time analysis and management.



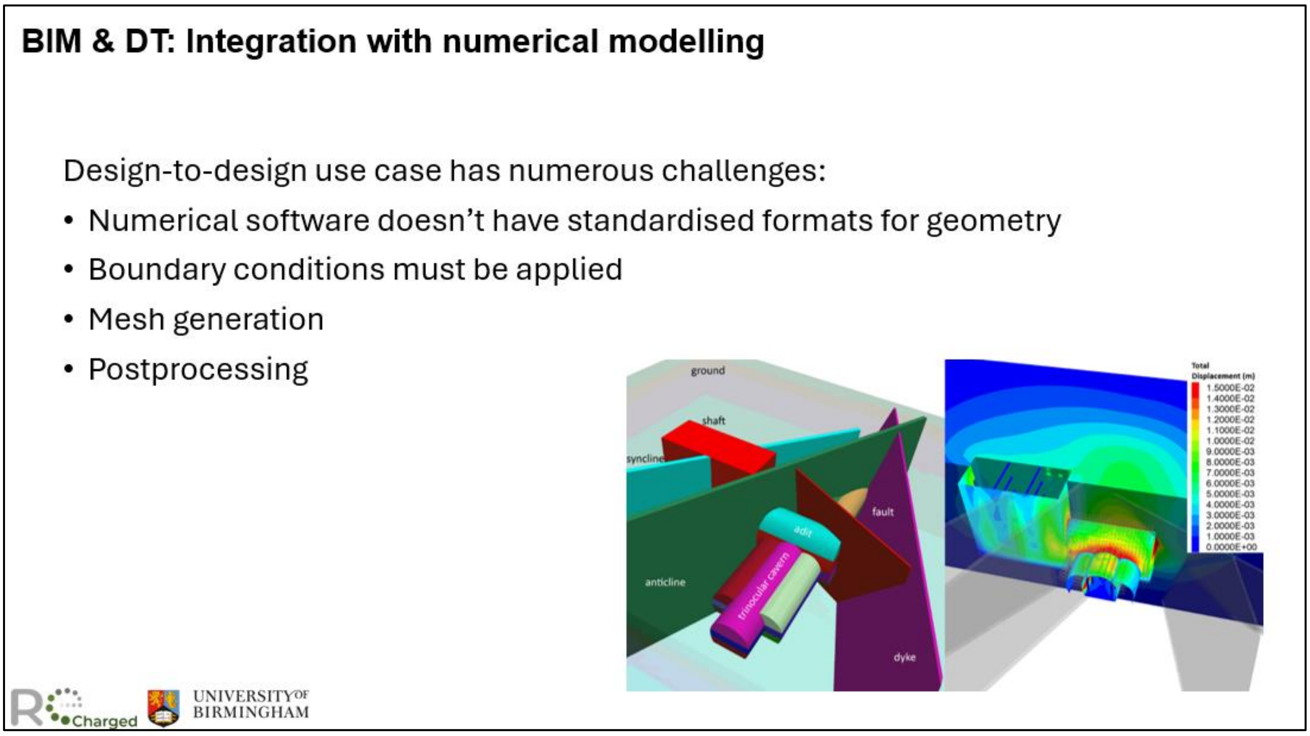
Transitioning from BIM to a Digital Twin involves progressive enhancements in functionality and interactivity. At Level 1, BIM serves as a static 3D visualization tool, providing basic project representations. Moving to Level 2, BIM supports simulations based on static information, enabling deeper analysis of design aspects. Level 3 integrates BIM with IoT, incorporating real-time sensor data to reflect current conditions. At Level 4, real-time predictions are made possible through advanced algorithms, aiding in proactive decision-making. Finally, Level 5 represents the Digital Twin, a fully dynamic and interactive model that continuously updates and evolves with real-world changes, offering comprehensive insights and management capabilities.



All the function of Level 1-4 are including, and enables with an intelligent feedback control system to automatically take actions based on optimized results and control strategies: Visualization of real-time built environment data; Predictions based on dynamic building information associated with real-time data sensing; Automatic control feedback with optimized management strategies to introduce interventions in the built environment.



BIM applications extend beyond static models to include integration with numerical modeling for precise simulations, support for sustainability assessments to evaluate environmental impacts, and the creation of Digital Twin prototypes for real-time updates and enhanced management. These applications enable more informed decisions and efficient project lifecycle management.

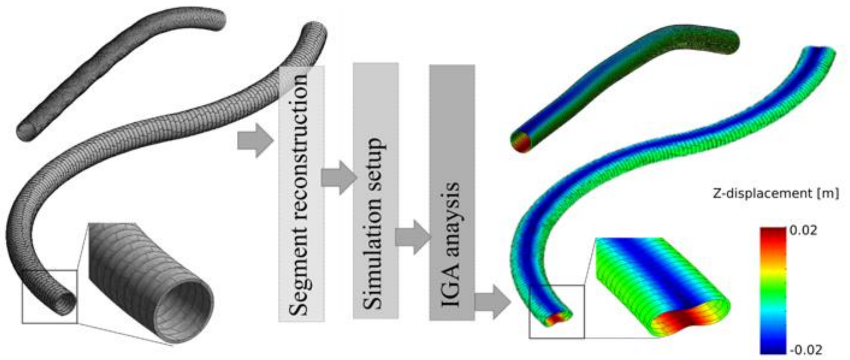


Integrating BIM with numerical models in design-to-design workflows presents several challenges. Numerical software often lacks standardized formats for geometry, complicating data exchange and consistency. Boundary conditions, crucial for accurate simulations, must be meticulously defined and applied to ensure model accuracy. Mesh generation, the process of subdividing the model for analysis, can be complex and time-consuming, requiring careful adjustment to balance detail and computational efficiency. Additionally, post-processing of results is essential for interpreting and validating simulation outcomes. Addressing these challenges requires robust integration strategies to streamline data transfer, enhance model accuracy, and facilitate effective analysis across platforms.

BIM & DT: Integration with numerical modelling

Opportunities:

- To adopt interoperability principles
- To go for open-source platforms with advanced methods: IGA, CutFEM



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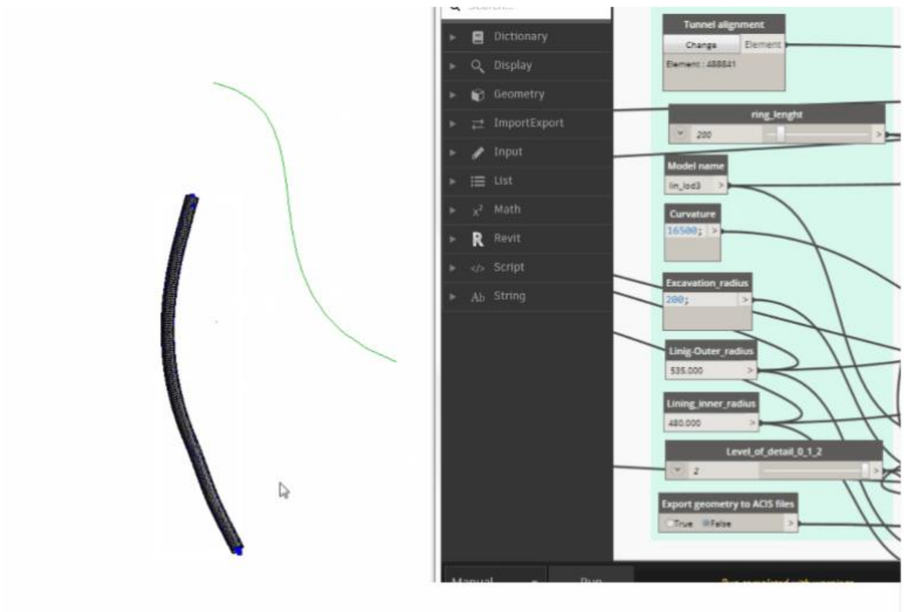
However, integrating BIM with numerical software also presents significant opportunities for advancing design and analysis (Ninic et al., 2020a). Adopting interoperability principles can bridge gaps between disparate systems, ensuring seamless data exchange and consistency. Embracing open-source platforms offers access to advanced methods like Isogeometric Analysis (IGA) and CutFEM, which enhance the precision and flexibility of simulations. IGA leverages smooth geometric representations from BIM for more accurate analysis, while CutFEM handles complex geometries and boundary conditions effectively. These integrations can streamline workflows, improve model accuracy, and foster innovation by combining the rich detail of BIM with the computational power of modern numerical techniques.



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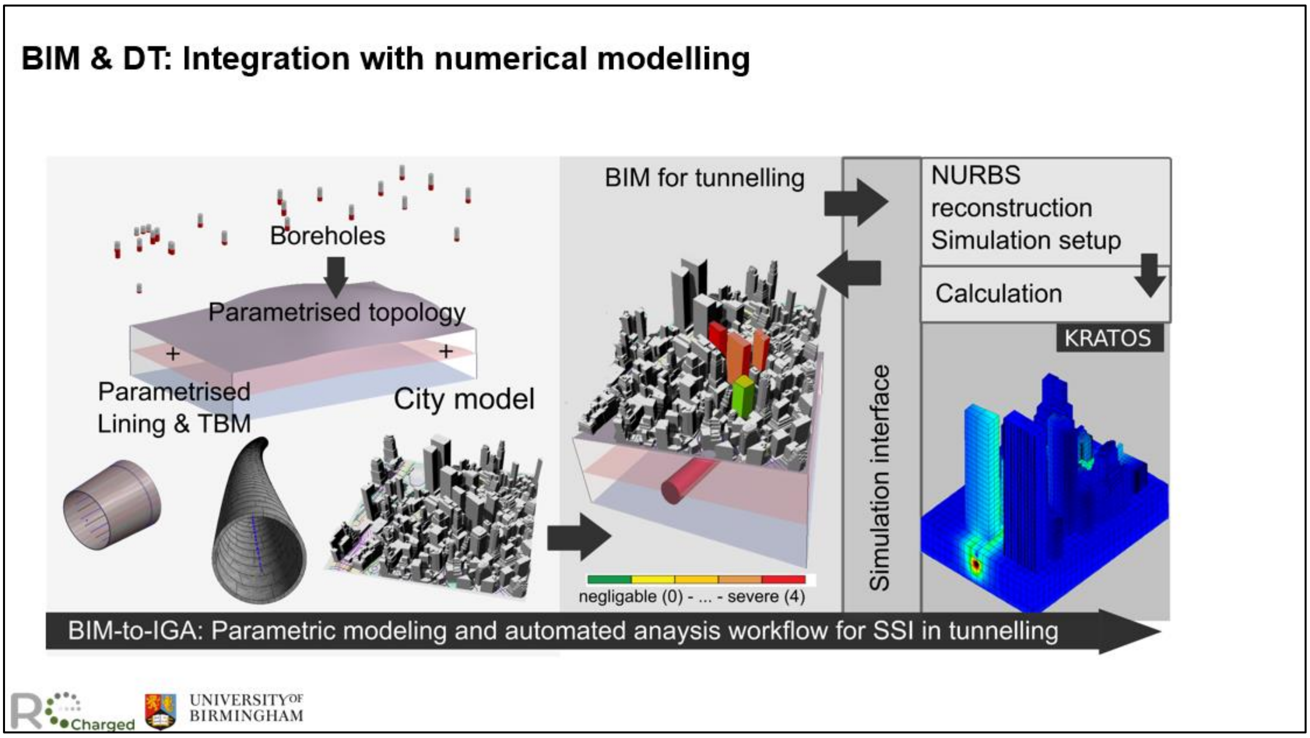
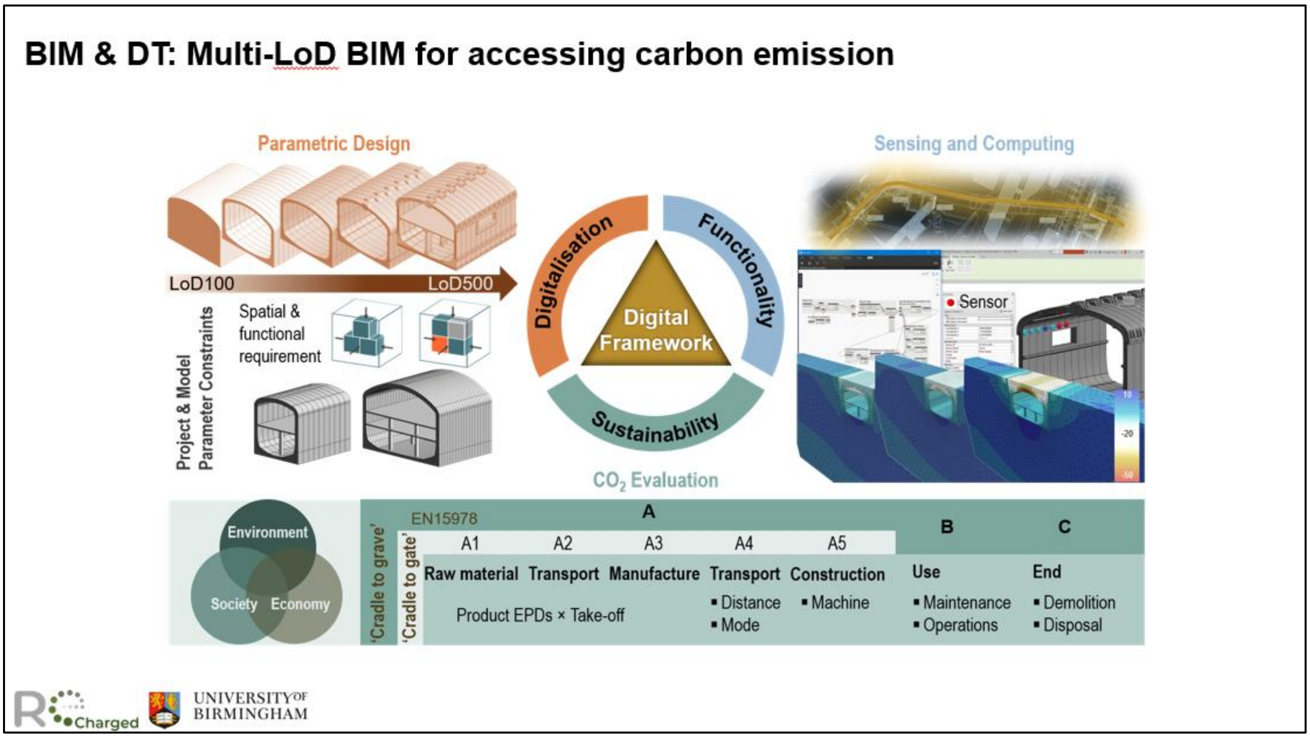
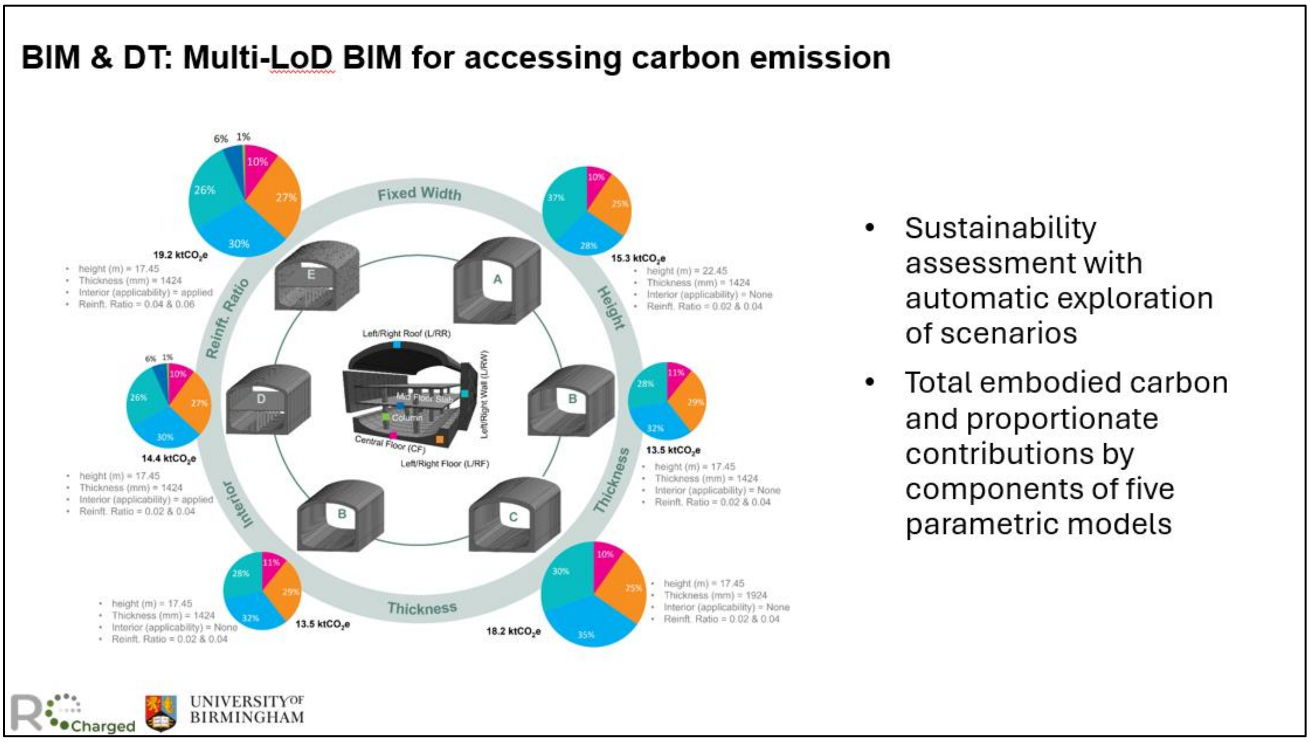
This video shows a workflow that fully automates the entire process, from model generation and numerical simulation export to result visualization, ensuring seamless and efficient operations without manual intervention.



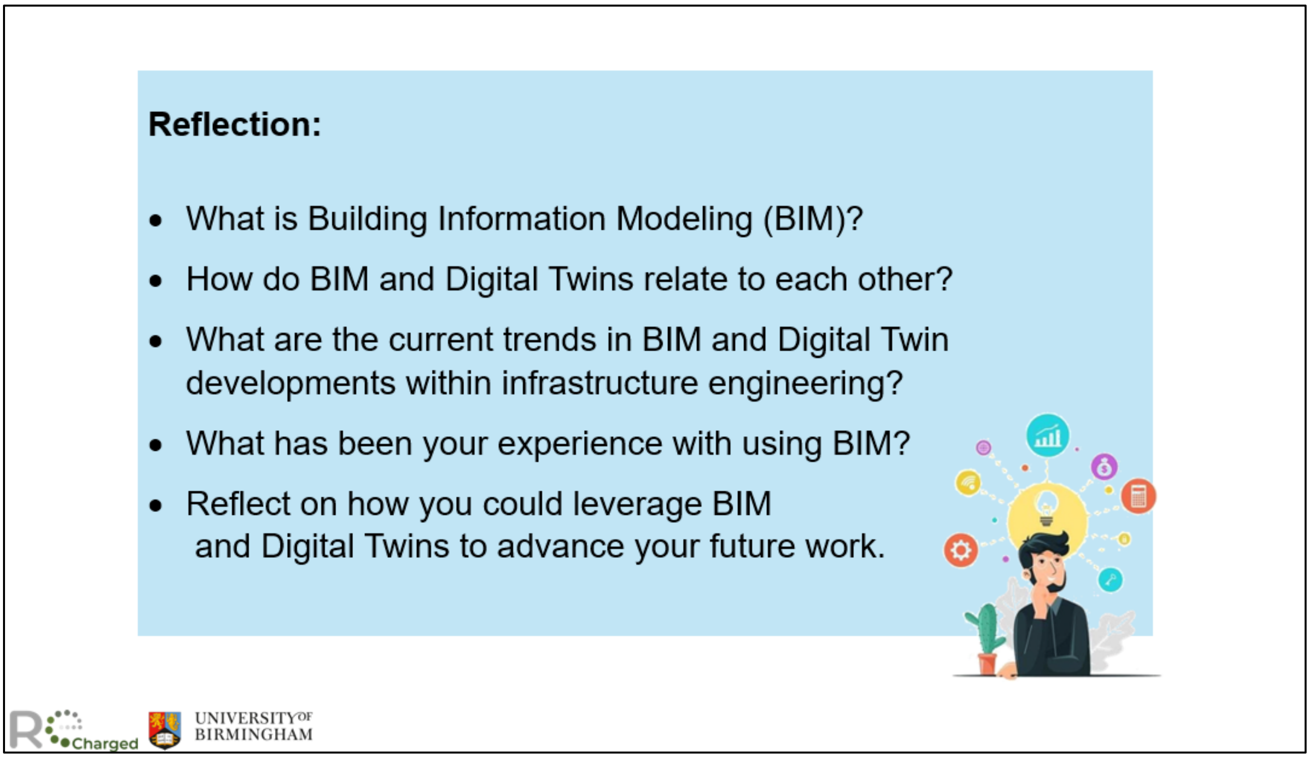
In the context of a City BIM model, opportunities arise for automating workflows that streamline the entire process. This includes fully automatic generation of the city model, seamless export, execution of numerical simulations, and visualization of results. This approach allows us to run scenarios and analyze the impact of tunneling on buildings, providing valuable insights into potential effects and facilitating better planning and decision-making.



Digital twin-enabled framework for integrating digitalisation, functionality and sustainability of underground station. BIM-based multi-Level of Development (LoD) parametric modeling facilitates detailed design, analysis and visualization of prefabricated metro stations, allowing for precise planning and execution (Huang et al., 2023). Explicit parametric relationships and constraints enable adaptive designs that can evolve with project needs. An emphasis on upfront carbon assessment, measured in kgCO2e, ensures sustainability by evaluating the minimum life cycle scope of embodied carbon. Integrating embodied carbon assessment with prefabricated construction feasibility further enhances this approach, promoting efficient, eco-friendly solutions and reducing overall environmental impact.



Sustainability assessment now features automatic scenario exploration, evaluating total embodied carbon and its component-wise contributions across five parametric models. This approach provides insights into the environmental impact of different design variations, facilitating more informed decisions to enhance sustainability in construction projects. The pie charts show A1-A5 embodied carbon and their proportionate contributions, with colors representing component markups, across five parametric models (I, II, III, IV, and V) all with a fixed total width of 25 m. These models vary in total height, lining thickness, interior features, and steel reinforcement ratio. For each comparison, the parameter being altered is highlighted between the different design variations (Huang et al., 2023).



At last, at the end of this activity, you should reflect on BIM as a digital representation of a assets's physical and functional characteristics. How BIM and Digital Twins are related? Reflect on the current trends in BIM and Digital Twins. Furthermore, reflect on your experience with BIM, consider how leveraging these technologies can streamline project management, improve collaboration, and optimize maintenance processes. By how by adopting BIM and Digital Twins, you can enhance efficiency, accuracy, and decision-making in your future infrastructure projects.

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