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Automated extraction of geotechnical data from core photography for tunnelling projects using artificial intelligence

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ABSTRACT: Geotechnical data is critical for safe and efficient tunnelling, but manual core logging is slow, labour-intensive, and subjective. This paper presents an automated approach for extracting geotechnical parameters from core photography using computer vision. The Datarock Core platform derives datasets such as Rock Quality Designation (RQD) and dominant colour from standard drill core images. In a Sydney Metro West case study, automated RQD was compared with manually logged intervals, showing strong correlation in high-quality rock (RQD 75–100) and greater variance in lower-quality intervals, primarily due to interpretation differences. Dominant colour extraction highlighted lithological boundaries, even from legacy imagery not captured for this purpose. These results demonstrate that automated analysis can produce accurate, consistent, and high-resolution datasets, improving geotechnical confidence and enabling faster, more objective decision-making. The method supports integration into tunnelling workflows from planning to construction, offering a scalable solution to the limitations of traditional logging.

1 INTRODUCTION

Geotechnical data plays a critical role in the design, safety, and risk assessment of tunnelling projects. Accurate and detailed geotechnical information is essential for understanding the physical properties of rock masses, which influence key factors such as stability, stress conditions, and excavation strategies. Traditional methods of collecting this data, such as manual core logging and visual inspection, are often time-consuming, subjective, and prone to error. These challenges are further exacerbated by the shortage of skilled professionals in the field, making manual data collection even more inefficient (Jaeger & Cook, 1963).

The process of manually analysing core samples, such as assessing rock quality, fracture frequency, and mineral composition, requires significant expertise. However, the inherent subjectivity of human observation and the time-consuming nature of manual logging can lead to inconsistencies in the data, hindering reliable decision-making (Hancock et al., 2014). Furthermore, this traditional approach struggles to keep pace with the rapid throughput demands of modern tunnelling projects, where quick and accurate data is crucial for timely project execution.

In recent years, the integration of artificial intelligence, particularly computer vision and machine learning technologies, has emerged as a promising solution to these challenges. These technologies can automate the extraction of geotechnical data from core images, enabling the rapid and consistent identification of key parameters such as Rock Quality Designation (RQD), fracture frequency, and colour variations indicative of geological features. By processing high-resolution images of drill cores, computer vision systems can automatically detect visual patterns, such as fractures and joints, that are essential for evaluating rock mass stability and stress conditions in tunnelling environments.

Automating the extraction of geotechnical data not only improves the speed and consistency of the data collection process but also ensures a more standardised approach, reducing human error and increasing the reliability of the collected data. This advancement has the potential to significantly enhance the accuracy of geotechnical assessments, aiding in better risk management and structural modelling throughout the lifecycle of tunnelling projects. Moreover, the automated system can seamlessly integrate into various stages of tunnelling operations, from project planning to construction, offering timely, consistent and actionable insights, ultimately allowing the engineer to make more confident decisions over the life of the tunnelling project.

This paper proposes a novel approach to automating geotechnical data extraction using the Datarock Core platform, which uses artificial intelligence (AI) to photolog. The software was then used to assess publicly available datasets from the Sydney Metro West tunnelling project for two datasets: Rock Quality Designation (RQD) because it is a very commonly logged dataset, and core dominant colour because it can often reflect key geological features that are not always logged by civil and geotechnical engineers.

Previous attempts at automated core analysis include image segmentation and edge detection for fracture mapping (Scott et al., 2014; Carlson et al., 2016), though these often required manual correction. More recent work applies convolutional neural networks for lithology classification (Kanazawa et al., 2019) and object detection for fracture identification (Ma et al., 2021). Commercial platforms such as Coreshed enable digital core storage and basic measurements but lack fully automated extraction of metrics like RQD. In contrast, this study uses deep learning models—Mask R-CNN for segmentation and RetinaNet for marker detection—to deliver high-accuracy, fully automated parameter extraction from standard core photography.

2 SYDNEY METRO WEST PROJECT

The Sydney Metro West project is delivering a new 24-kilometre underground metro line between Westmead and the Sydney CBD to double rail capacity and reduce travel times. Construction involves twin tunnels bored by large tunnel boring machines, nine new underground stations, and supporting infrastructure such as a maintenance facility at Clyde. The project traverses complex geology, requiring advanced tunnelling and ground treatment methods, with cross passages spaced every 240 metres for safety and ventilation. (Sydney Metro, 2023)

The alignment crosses Triassic Hawkesbury Sandstone, Ashfield Shale, and Mittagong Formation, as well as Quaternary alluvium in valley areas. Hawkesbury Sandstone is strong and durable but locally jointed, affecting cutter wear. Ashfield Shale is weaker and prone to slaking, requiring careful face support. The Mittagong Formation has variable strength and permeability, posing settlement risks. Alluvial deposits are soft clays and loose sands with high compressibility and groundwater inflow potential (Herbert & Helby, 1980; Sydney Metro, 2020).

Key engineering challenges include tunnelling beneath dense urban environments and protecting heritage structures, while sustainability targets are being prioritised throughout construction. Major tunnelling commenced in 2023, with system integration and station fit outs progressing towards a targeted opening by 2032.

3 METHOD

3.1 Overview

This section details the procedure for extracting two key datasets, RQD and dominant colour, from core photography. These examples demonstrate the potential of this technology for geotechnical rockmass characterisation. The necessary pre-processing steps for transforming raw images into analytics-ready data are also described.

RQD and Dominant Colour were selected to effectively illustrate how a well-structured AI workflow can derive valuable insights from core images.

Rock Quality Designation (RQD) quantifies rock mass quality based on the percentage of intact core segments exceeding 100 mm within a specified interval. It is a crucial indicator of jointing and fracturing, vital for assessing rock mass behaviour. As a widely adopted geotechnical parameter, RQD routinely informs the design of tunnels, foundations, and slopes.

Datarock's dominant colour tool identifies a single representative colour for each core image row. This generates a simplified and uniform visual output compatible with most 3D modelling platforms, improving visualisation and integration within geological models. Given that colour often correlates with significant geological attributes like lithology, oxidation, and mineralogy, dominant colour is a valuable asset for interpreting rock characteristics and stratigraphy.

3.2 Depth registration

Depth registration is essential for accurately assigning depths to core images. This allows for precise identification of geological structures (e.g., joints) and facilitates reliable comparison and calibration with other downhole datasets.

The process of preparing 'analytics-ready' images involves several preprocessing steps, including six chained individual Mask R-CNN (a two-stage region-based convolutional neural network) instance segmentation models which are used to identify the following features within the raw images: core trays, core tray rows, identification of coherent, broken rock, core blocks and empty tray. All of these models have been fine-tuned by Datarock on thousands of drill core images.

Using these predictions, we can quantify compaction in broken rock, core loss compensation, and optical character recognition for reading handwritten depths on the core or core blocks. In this study, the Datarock Core platform was utilised for core row image preparation and depth registration. Figure 1 provides examples of depth-registered rows and their assigned depths, including depths based on handwritten metre marks (green markers) and inferred depths (yellow markers).

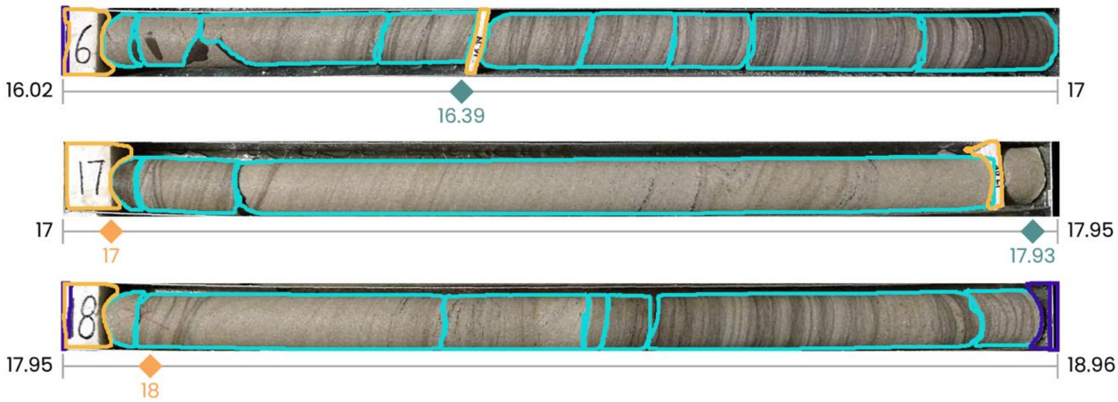


Figure 1. Example of depth-registered core rows generated by the Datarock Core platform.

3.3 Rock Quality Designation

The method developed involves several steps to extract RQD from core photography. As described above, RQD measures rock mass quality based on the percentage of intact core pieces >100 mm recovered from a borehole.

The first step is to take the raw image of each row and identify all the pieces of coherent, or whole, core using a segmentation model

A Mask R-CNN model is used to segment individual pieces of coherent/intact core, in the image by detecting and classifying each segment as a distinct object, generating instance-specific masks that outline the boundaries of intact core. This enables automated, pixel-level identification of core pieces, which is essential for downstream analysis. The primary metric we use for these models is lengthwise precision as understanding the length of each piece of core is important for calculating depth and RQD. The average lengthwise precision for the models on this dataset was 0.95 which is very good.

Figures 2 and 3 show the row image and identification of coherent pieces respectively.

Figure 3. Raw cropped row image

Figure 2. Coherent rock computer vision model predicts a polygon around each piece of core

Step 2: Identifying mechanical breaks

Drilling and core handling can produce artificial fractures, commonly referred to as induced, mechanical, or driller's breaks. As Huaman et al. (2018) observed, distinguishing these from natural fractures typically requires physical inspection for features such as surface profile, weathering, or staining. Image-based identification of mechanical breaks is challenging, particularly when image quality varies. In standard practice, mechanical breaks are marked manually on the core with a distinctive symbol. In our methodology, all fractures are considered natural unless explicitly marked as mechanical.

To detect these markings, we trained a RetinaNet (Lin et al., 2017) object detector to identify hand-drawn indicators adjacent to mechanical breaks in core photography. The model learns to detect and localise these distinct visual cues, outputting bounding boxes around them. This enables automated association of mechanical break markers, allowing them to be considered in downstream analysis. Figure 4 illustrates an example of successful marker detection.

Figure 4. Mechanical break model predicts a box around each mechanical break mark

Step 3: Calculate RQD

Now that all the pieces of core and mechanical breaks identified, they can utilise these to calculate RQD. Using the mechanical break marks, adjacent core pieces are "joined" to ensure only natural breaks are considered.

Since all the row images has been accurately depth registered, each piece of core is measured and classified as less than, or greater than, 100mm long and display those outcomes on the core photography.

Figure 5. Each piece of core is measured and classified as less than or greater than 100mm

Finally, the pieces greater than 100mm are utilised as per the equation below.

$$RQD = \frac{\Sigma length\ of\ core\ pieces > 100mm}{Total\ interval\ length} \times 100\%$$

Equation 1. RQD calculation as per the Deere (1964) method.

The results generated are in the form of a CSV, like standard core logging. It includes headers such as hole_id, depth_from, depth_to, rqd_m, rqd, mechanical_break_count and coherent_rock_length. This enables direct importing into any standard geotechnical analysis software package.

3.4 Dominant colour

Extracting a single colour, that is most representative of an image, involves a clustering exercise of every pixel within the image. The following steps are taken on each image, in this case each row image:

1. Taking the depth registered row image
2. Extract every pixel from the image and plot each RGB triplet onto a 3-axis plot.
3. Cluster all the RGB values into five clusters.
4. Determine the cluster with the highest number of pixels. This is the dominant cluster.
5. Find the geometric centre of the dominant cluster. The R, G and B values of this point is the Dominant Colour for the interval, in this case the row image.
6. Convert the RGB value to a hex value.

The method developed involves several steps to extract RQD from core photography. As described above, RQD measures rock mass quality based on the percentage of intact core pieces >100 mm recovered from a borehole.

Figure 6. Raw cropped row image

Figure 7. Dominant colour representation of the image in Figure 6. (R=163, G=133, B=113)

4 RESULTS AND DISCUSSION

In this section, the results are compared against a real-world project – the Sydney Metro West project, Eastern Tunnelling Package. The core photography and geotechnical logs are publicly available data on the Geological Survey of New South Wales' MinView application. The package consists of 49 drill holes for a total of approximately 2,000m of core. It should be noted that the core photography was not captured for this use.

4.1 Rock Quality Designation

RQD comparison has been completed in two ways:

1. Downhole plots; and
2. Scatter plot of Logged vs Datarock RQD.

4.1.1 *Downhole plots*

As can be seen in the figure below, there is a strong correlation between the site logging (red) and the results produced by Datarock Core (blue). A more detailed review of intervals that vary significantly is also shown below.

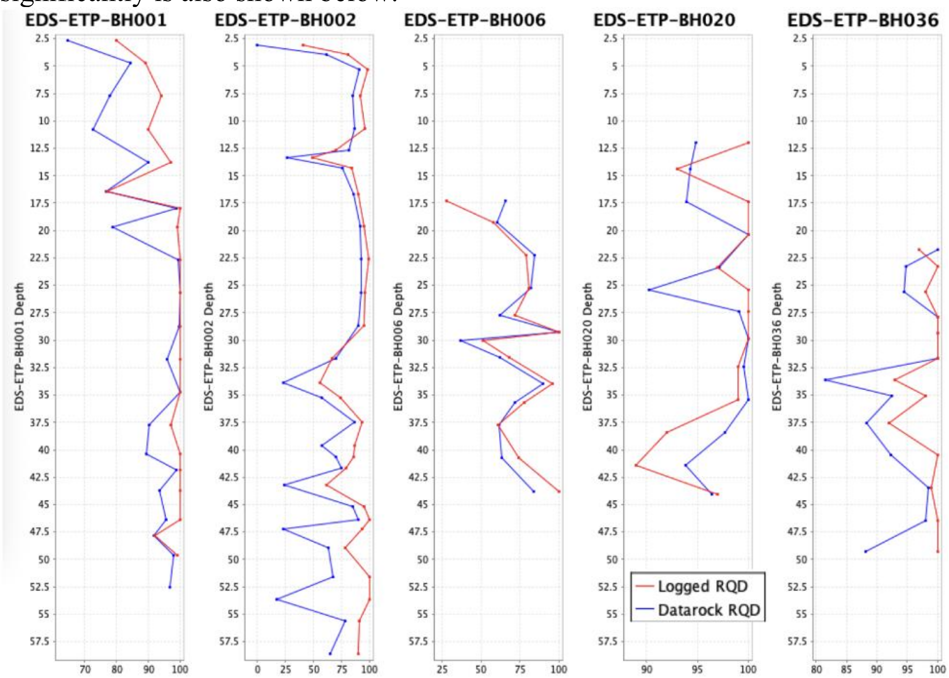
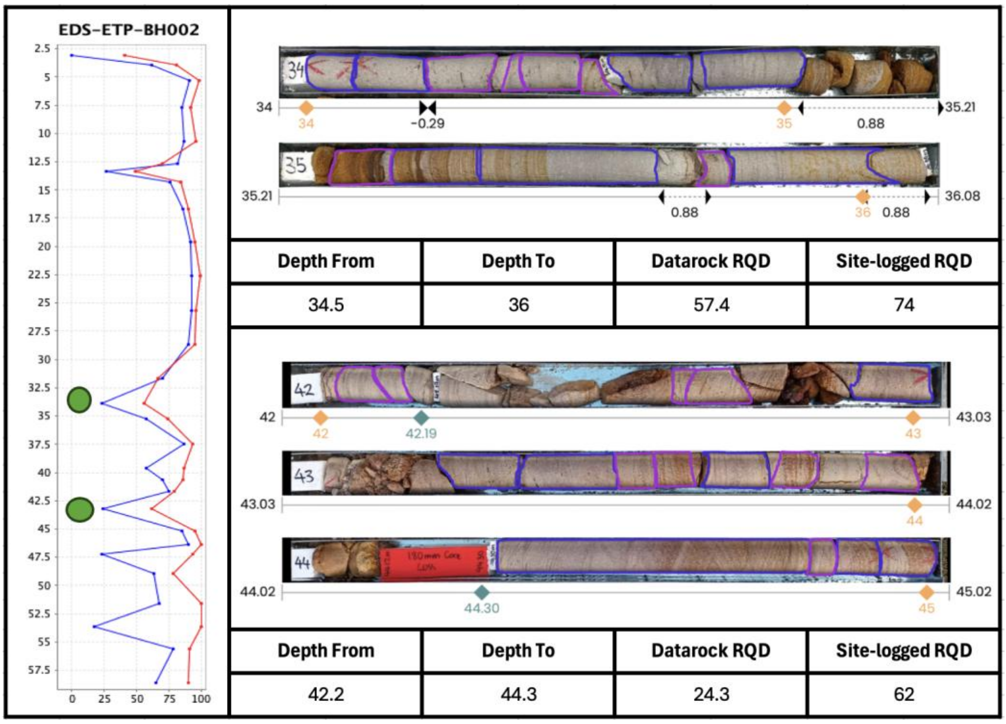


Figure 8. Example downhole plots for five of the processed holes.

Intervals within borehole EDS-EPT-BH002 that vary significantly from site logging are assessed in detail below.



Depth From	Depth To	Datarock RQD	Site-logged RQD
34.5	36	57.4	74

Depth From	Depth To	Datarock RQD	Site-logged RQD
42.2	44.3	24.3	62

Figure 9. Detailed interval comparison of logged vs Datarock RQD. Core pieces <100mm are shown in pink, >100mm shown in blue.

In reviewing the predictions on the core photography, the polygons are generally representative of the features within the image. There are some core pieces that are near the 100mm threshold and understandably loggers will make judgement calls either way. Given the predictions appear to be accurate, it is deemed that the Datarock Core results are more accurate than the logging.

4.1.2 *Scatter plot of Logged vs Datarock RQD*

In addition to reviewing downhole plots, a total of 902 intervals are compared in the figure below.

- Strong agreement is evident in the highest-density cluster of points, located in the top-right quadrant, particularly within the 75–100 RQD range. This suggests close alignment between logged and Datarock RQD values in high-quality core zones, where recovery is near complete and features are easier to interpret visually.
- Greater variance is observed at lower RQD values, where both manual logging and the automated system may under- or overestimate values. This is expected: fragmented or broken core presents challenges for automated segmentation, while human loggers may skip precise measurements of every fragment, unlike the systematic approach of the AI.
- Despite increased scatter in the lower RQD range, the overall distribution remains closely aligned with the 1:1 line, indicating strong correlation between logged and Datarock-calculated RQD, especially in the intervals of most engineering interest.

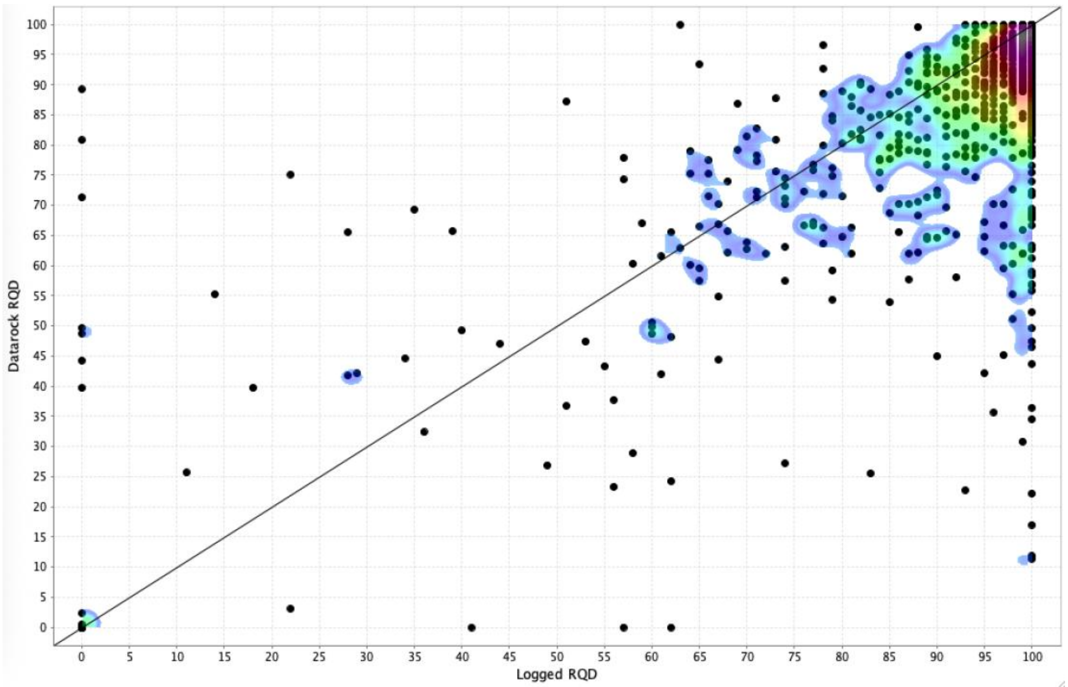
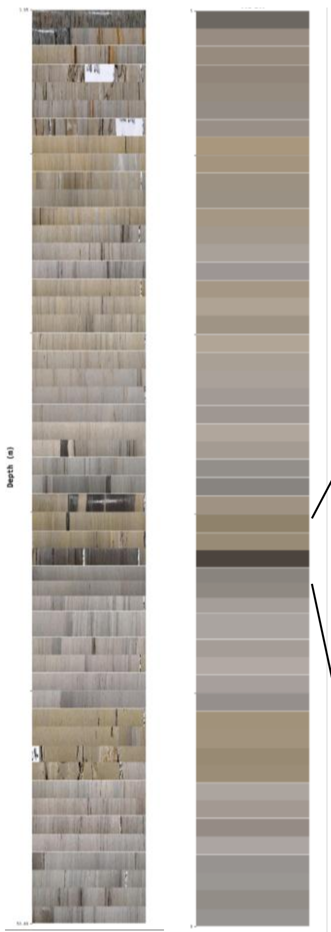


Figure 10. Comparison of manually logged RQD values and automated RQD extracted using the Datarock Core platform. Heatmap provided to indicate data point concentration.

4.2 Dominant colour



Borehole EDS-ETP-BH061 provides an example of the results. The left strip image is a composite of stitched cropped row images. The right strip image displays the dominant colour representation for each row. The geological variability is evident in the images. When this data is viewed in a long section along a corridor or across a mineral deposit, the advantage of reducing images to a single representative value becomes clear.

The image below shows that the layer of interbedded siltstone and sandstone present within the sandstone that is clearly visible in the colour log.

It is noted that these results are completed on the row images for ease of comparison, but if more granular detail was required, it could be processed on, say 0.5m intervals.

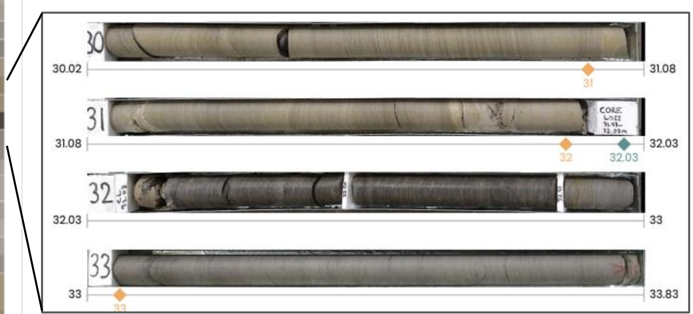


Figure 11. Example of dominant colour extract. Left image: row image composite, middle image: dominant colour representation, right image: close up of row images showing changes in lithology.

5 CONCLUSIONS

This study shows that computer vision can automate extraction of key geotechnical parameters—such as RQD and dominant colour—from standard core photography. The approach improves accuracy and consistency over manual logging while reducing subjectivity and labour.

In the Sydney Metro West case study, automated RQD closely matched manual logs in high-quality rock (RQD 75–100) and diverged more in fragmented intervals. Dominant colour analysis clearly highlighted lithological boundaries, even from legacy imagery.

Using deep learning (Mask R-CNN and RetinaNet) enables fully automated, high-precision extraction compared with earlier semi-automated methods. The structured datasets integrate directly into geotechnical models, supporting faster analysis and consistent decisions.

Future work should improve fracture detection in fragmented core and conduct controlled experiments where site logs have been reviewed for quality. Core photography should be captured specifically for computer vision processing, ensuring higher image quality and enabling more reliable comparisons with manual logging.

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