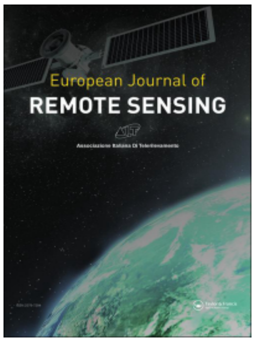

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A systematic review of machine learning-based remote sensing data analysis for geological and mined materials characterisation

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ABSTRACT

The mining industry is undergoing a significant transformation, driven by advancements in remote sensing technology that enable the collection of large-scale data on the geological and geotechnical properties of mined materials. As the volume and complexity of data generated by advanced imaging methods continue to increase, traditional analytical techniques struggle to effectively process and interpret this information. To explore current practices and the application of machine learning in interpreting complex imaging data for mine material characterisation, a review of 92 studies from 2004 to 2024 was conducted. This review focuses on key aspects of mining operations, including exploration, extraction, and waste management. It highlights the unique challenges inherent in the mining environment—particularly the heterogeneous nature of geological and mined material samples, which can result in spurious absorption features that complicate data analysis. In addition, it discusses the challenges posed by high-dimensional data resulting from sensor capabilities, as well as the cost and time constraints associated with existing algorithms. Ultimately, the review underscores both the opportunities and limitations of current machine learning approaches in analysing geological and mined materials, emphasising the need for ongoing research to overcome these challenges and fully utilise machine learning-based remote sensing in the mining sector.

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Machine learning, exploration; extraction; waste management; sustainable practices

Introduction

The mining industry is shifting towards the adoption of machine learning and image-based material characterisation, spurred by advancements in remote sensing technology that enhance accessibility and safety. This transition is replacing traditional methods, such as laboratory analysis and visual inspections, with more efficient techniques that provide critical insights into the geological and geotechnical properties of materials (El-Omairi & El Garouani, 2023; Qin & Li, 2023). Machine learning-driven image analysis plays a vital role throughout the mining process, from mineral identification during the exploration phase (Shirmard et al., 2022) to ore quality evaluation during and after extraction (Xu et al., 2019), as well as characterising waste and its associated geotechnical properties (Thiruchittampalam et al., 2024).

Recent developments in the characterisation of mining materials have been greatly enhanced by sophisticated remote sensing techniques, including multispectral and hyperspectral imaging (Birdwell et al., 2020; Esmaeili et al., 2024; Karan et al., 2016; Kirsch et al., 2018), along with their downstream applications (Vignesh & Kiran, 2020). The operability of these advanced sensors in mining environments is particularly advantageous, as the outcomes depend heavily on data with enhanced spatial-spectral-temporal resolutions, which are crucial due to the dynamic nature of mining operations. The comprehensive data produced by these techniques, encompassing both compositional and morphological aspects at various scales, facilitates high-resolution mapping of geological variations and geotechnical properties.

However, the increased complexity of the data has resulted in a surge in data volumes and dimensionality (Taylor & Vukovic, 2001), leading to a more intricate and sparse feature space. To navigate this complexity without presuming specific data distributions, new image analysis techniques, particularly those based on machine learning and deep learning classification (Alzubaidi et al., 2021; Madhuanand et al., 2021), have emerged. These methods offer robust capabilities for extracting and refining knowledge from remote sensing data (Jooshaki et al., 2021), with their effectiveness further enhanced by specific methodologies employed in pre-classification (Jakob et al., 2017). The mining and remote sensing communities are actively working to

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advance these image analysis methods, from pre-processing to classification.

The outcomes of these advancements have various applications in mining, including the development of mining plans that serve as operational and management blueprints for mines (Carabassa et al., 2020; Y. Fu & Aldrich, 2020; Liu et al., 2023). Consequently, advancements in machine learning-based image analysis of remote sensing data present transformative opportunities for geological and mined material characterisation (Aznar-Sánchez et al., 2018; Mou et al., 2023; Worlanyo & Jiangfeng, 2021), significantly enhancing the efficiency, sustainability, and safety of mining operations (Abaidoo et al., 2019).

Over the past two decades, a diverse array of machine learning and image analysis techniques has been applied to remote sensing data for geological and mined material characterisation, driven by technological advancements and increased computational power. These techniques have evolved, with newer methods providing improved accuracy, speed, and versatility. This systematic review aims to evaluate these techniques, offering insights into the current state of machine learning-based geological and mined material characterisation and identifying potential opportunities for further innovation and improvement within the domain of image analysis for geological and mined material characterisation. Staying abreast of developments in machine learning and image analysis can greatly enhance the efficacy of the material characterisation process.

The scope of this review is focused on the exploration, extraction, and waste management aspects of mining, which are critical stages where accurate and efficient geological and mined material characterisation can significantly impact the triple bottom line. However, this review excludes material characterisation after mineral processing and tailings characterisation because these processes introduce external variables that alter the material properties, making the analysis significantly different from raw material assessment. The complexity and specificity of these modified materials warrant a separate in-depth study, distinct from the scope of this review.

Research methods

Scope of the review

In this study, we conducted a comprehensive literature review with a systematic approach, utilising the Scopus database. The review involved exploration of literature spanning a 20-year period, from 2004 to 2024. Imaging for material characterisation in mining began in the late 1980s with the AMIRA P243 project. This project catered to the increased gold exploration using the Landsat Thematic Mapper and SPOT imaging satellites, which were introduced during that period (Cudahy, 2016; Gabell et al., 1992). Further, the efforts of the researchers to utilise remote sensing techniques in the early 1980s are highlighted in the review by Goetz et al. (1983). The review is limited to the past 20 years to ensure the relevance and recentness of tools and techniques in deriving potential new strategies for machine learning-based characterisation of geological and mined materials.

After conducting the initial search on Scopus, a two-stage process was employed to select papers for the review. In the first stage, papers meeting the specified Scopus search criteria were chosen if they were relevant to the fields of machine learning-based image analysis and geological material characterisation related to mining. This included peer-reviewed journal articles, conference papers, books, magazines/bulletins, and scientific reports. In the second stage, papers were shortlisted according to their suitability to the review and based on the following criteria:

(a) The study focused on the characterisation of geological and mined material using remotely captured images in exploration, extraction and waste management coupled with analysis grounded in machine learning algorithms.
(b) The study aimed to characterise mined materials to provide insights into geological or geotechnical aspects.
(c) The study centred around panchromatic, red-green-blue (RGB), multispectral and hyperspectral images.

A considerable quantity of image analysis and computer vision papers that lacked direct relevance to the mining domain were excluded. Subsequently, to ensure comprehensiveness, additional searches were conducted on Google Scholar, Web of Science, and ScienceDirect using specific keyword combinations, including "image analysis", "computer vision", "machine learning", "deep learning", "exploration", "extraction", "mine waste" and "mining". This approach was employed to verify the Scopus search results and identify any potentially missed papers of relevance. The initial entries from each search were considered, and the process continued until no further pertinent entries were found after examining five pages within a search window. At the end of the filtering process, a total of 92 research articles (Figure 1) were retained for further analysis.

Meta-analysis of reviewed studies

A comprehensive meta-analysis has identified China (21), India (13), Germany (11), Australia (10), and the United States (9) as the foremost contributors to research in the field of machine learning-based image analysis for geological and

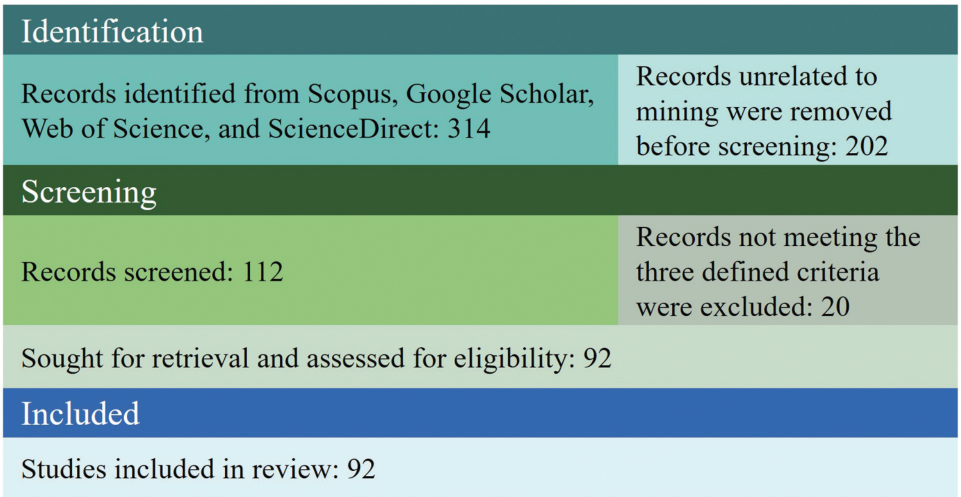

Figure 1. Flow diagram illustrating the process of article selection for the systematic review.

mined material characterisation, as depicted in Figure 2(a). From a temporal standpoint, the progression of studies in the field of mining, Figure 2(b) reveals a predominant focus on the exploration of materials. However, a shift in emphasis can be observed in recent studies, with an increasing number of them considering waste characterisation. This shift towards waste characterisation could be attributed to the growing emphasis on sustainability within the industry (Mancini et al., 2024). Moreover, there has been a noticeable surge in the number of published use cases for machine learning-based image analysis for geological and mined material characterisation since 2015. This trend can be attributed to advancements in sensors, increased accessibility to computational resources, and significant developments in image analysis techniques (Qin & Li, 2023).

Figure 3 provides a comprehensive overview of the focus areas in the reviewed studies, revealing that the 52 out of 92 are primarily centred on the characterisation of mining materials for exploration purposes. The escalating global demand for raw materials has heightened exploration efforts in the mining sector, supported by government incentives and reduced funding restrictions from geological agencies. However, post-transition to private ownership, funding for further research typically declines. Further examination of Figure 3(b,c) uncovers a broad application of RGB and hyperspectral data in these studies. There appears to be a preference for ground-based sensors, as they are cheaper to deploy. However, airborne sensors, which cover larger areas more efficiently, follow closely behind despite not providing the same level of detail.

Sensors utilised in the reviewed studies

Data serves as the fundamental element for machine learning-driven image analysis pertinent to geological and mined materials. Consequently, comprehending the sensors employed in the investigation, in conjunction with the data generated by these sensors, will establish a foundation for image analysis. Hence, a brief analysis of sensor and related data produced by these sensors (Figure 4) in reviewed studies are discussed in this section.

Red-green-blue (RGB) sensors. Ground-based RGB sensors have improved the precision and granularity of data registration and alignment in geological studies in mine environments. For instance, Kurz et al. (2008) utilised the Nikon D200 camera's calibrated lens for accurate registration and alignment of digital images with lidar point clouds and three dimensional (3D) models for geological study. The camera's known exterior orientation, in conjunction with the calibrated lens, facilitates the exact registration and alignment of the digital images with the lidar data. Higher resolution of the calibrated lens, compared to the spectral images, guarantees that the digital images offer comprehensive information to aid the validation and interpretation of spectral classification outcomes. The calibrated lens offers a known focal length and pixel scale, which are critical parameters for accurately converting image coordinates into the object coordinate system during the registration and alignment procedure. In essence, the RGB camera's calibrated lens is instrumental in achieving precise registration and alignment between the digital images and other data such as, the lidar data, thereby enabling the integration of spectral classifications with the 3D models. The D200, being an older digital single-lens reflex (DSLR) model, may have a limited ISO range and less effective noise reduction capabilities compared to more

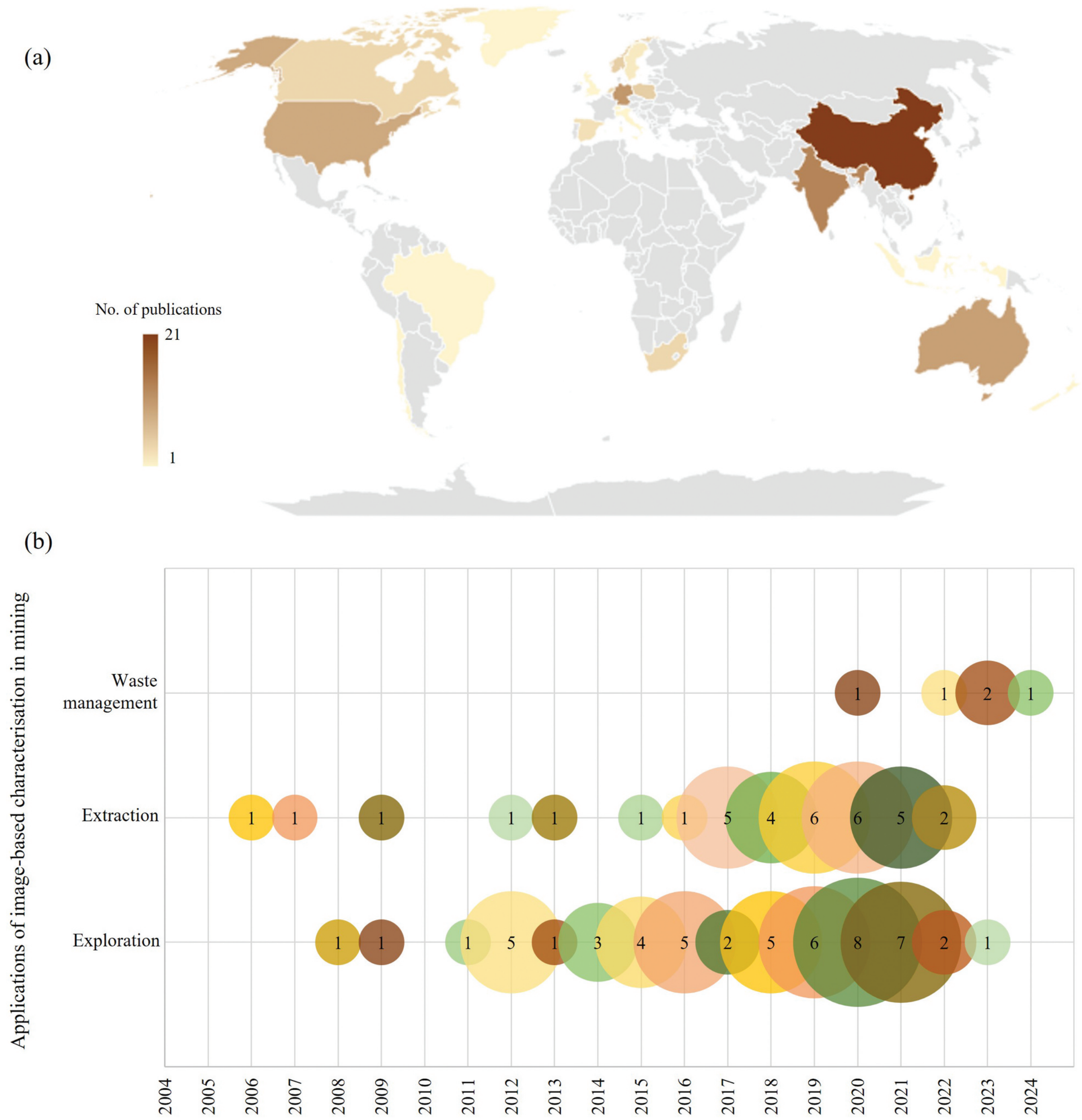

Figure 2. Distribution of publications (a) across different countries and (b) over the course of 20 years (2004–2024), which studied machine learning-based geological and mined material characterisation.

modern cameras, which could affect image quality in low-light conditions. Additionally, the fixed pixel count means that the camera has a finite resolution, which could limit the level of detail in photorealistic models when compared to higher-resolution sensors. Furthermore, the camera's reliance on calibrated lenses for image acquisition suggests that any imperfections in the calibration process could introduce errors into the photogrammetric models. In a more recent study by Kurz et al. (2022), the Canon EOS 6D camera, equipped with an 85 mm lens, was employed for data acquisition due to its full-frame DSLR capabilities that yield high-resolution images. The high-resolution images captured by the Canon EOS 6D camera were utilised to generate photorealistic 3D outcrop models using structure from motion (SfM) algorithm. These 3D models provided a geospatial framework for all outcrop data, facilitating the georeferencing and integration of hyperspectral imaging imagery and spectral mapping results. The detailed and continuous depiction of the outcrop exposure offered by the high-resolution images contributed to the precise mapping and analysis of the geological features and mineralogical variations in the mine areas.

In airborne image acquisition using RGB sensors, DSLR cameras were initially deployed on unmanned aerial vehicles (UAV). For example, Booysen et al. (2019) used the Canon S110 RGB camera to obtain geomorphic data, which had a resolution of 4.9 cm at

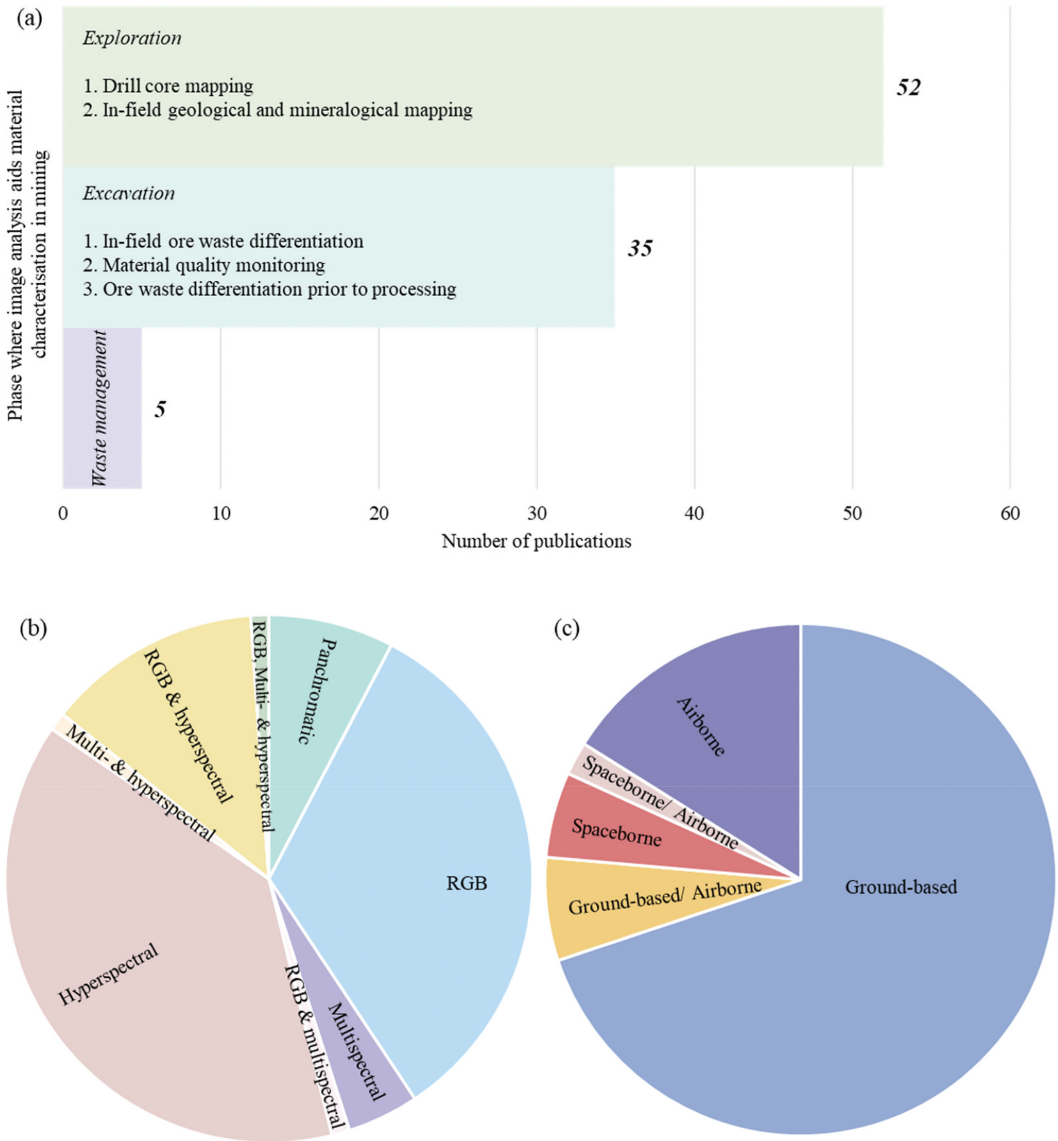

Figure 3. Distribution of studies according to the (a) phase of mining, (b) used data type (panchromatic, red-green-blue (RGB), multispectral, and hyperspectral data, or combination of these) and (c) deployed platform (ground-based, airborne, spaceborne sensors, or combination of these).

a 120 m flight altitude. This data was integrated with hyperspectral data because spectral data alone can lack sufficient discrimination potential due to spatial and spectral sensor resolutions or noise produced during acquisition. Over time, RGB sensors specifically designed for aerial surveys were introduced into geological and mined material characterisation. For instance, Yang et al. (2023) utilised a DJI Inspire 2 UAV with its default camera system, Zenmuse X5S, to investigate the use of RGB images for mapping small pit wall sections in mine sites (the ground sampling distance of the top pit was 0.626 cm/pixel and the pick pit was 0.574 cm/pixel). The study found that the UAV-acquired RGB images showed promise for simple geological settings. However, in more complex geological conditions, they deviated from human-labelled ground truth maps. Another study proposed a deep learning method for high-resolution geological mapping using the vast amount of data acquired using a DJI Phantom 4 Pro UAV with a 1-inch CMOS sensor (Sang et al., 2020). The studies highlight the progress made in the field of airborne RGB sensors and their application in characterising materials. This technological advancement has paved the way for high-resolution geological mapping and data gathering from mine sites that were previously inaccessible. Furthermore, it has opened up opportunities for the application of machine learning and deep learning techniques in the autonomous characterisation of geological and mined materials.

Multispectral sensors. When examining studies that utilises multispectral data, it becomes apparent that only a limited number of such studies exist. This scarcity may be attributed to the fact that multispectral data offers a lower spatial resolution in comparison to RGB data, as well as a reduced spectral resolution when contrasted with hyperspectral data. However,

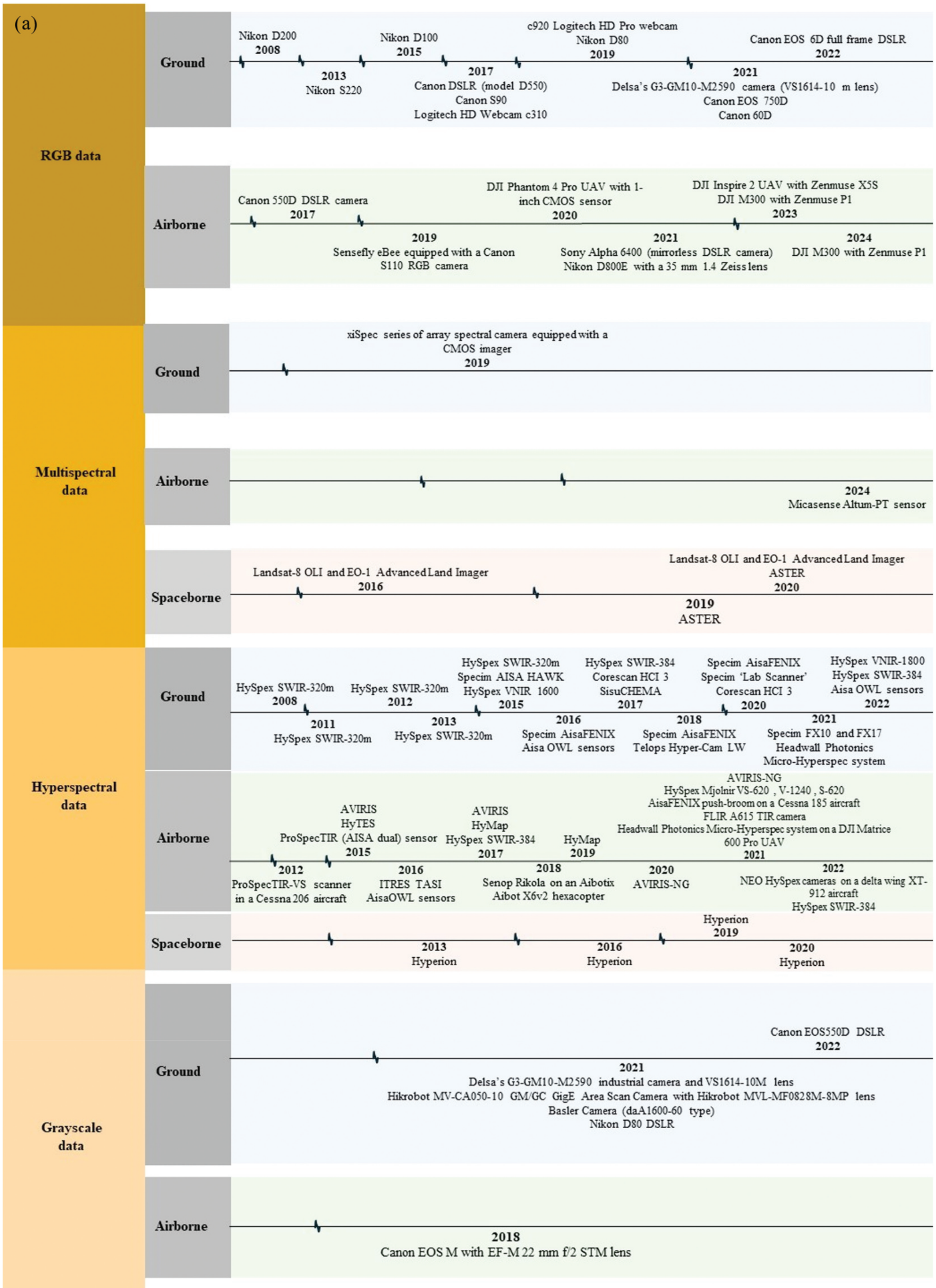

Figure 4. Sensors used in machine learning based geological and mined material characterisation along with the year of publication, the platforms where they are deployed, and the data acquired using these sensors.

the studies that employed multispectral data have demonstrated its advantages in geological and mined material characterisation. It serves as a bridge between RGB and hyperspectral data, offering a viable solution when there are limited computational resources, making the management of hyperspectral data or RGB data with extremely high spatial resolution challenging. For instance, to address the limitations of grayscale and RGB data in material characterisation, which stem from insufficient spectral information for detecting coal and gangue, Hu et al. (2019) investigated the use of ground-based multispectral imaging technology (MSI). Their MSI system, which included a filter device, a fixed focal length lens, and a xiSpec series of array spectral camera (MQ022HG-IM-SM5X5-NIR, XIMEA GmbH, Munster, Germany) equipped with a CMOS imager, was capable of capturing 25 wavelengths of imaging within the spectral range of 675 to 975 nm. The technology allows for the differentiation between coal and gangue at various wavelengths, with certain wavelengths providing better classification results. For instance, the ninth wavelength at 773.776 nm was found to be most effective in distinguishing between coal and gangue. Furthermore, it has proven to demonstrate high classification accuracy of materials in inaccessible areas of mine sites, particularly when only a few geological changes occur.

Thiruchittampalam et al. (2024) demonstrated that airborne multispectral data, captured using a Micasense Altum PT sensor with six bands, can assist in characterising coal spoil in dumps based on its geomechanical properties. They also reported that when this data is used in conjunction with textural features extracted from high-resolution RGB data, the accuracy of characterisation can be significantly improved. In addition, spaceborne multispectral imaging has been instrumental in early-stage exploration work and metallogenic prediction. Sensors such as Landsat-8 OLI and EO-1 advanced land imager (Mielke et al., 2016, Nair et al., 2020) as well as ASTER (Xu et al., 2019) have been utilised in these studies. The findings from these studies have confirmed the feasibility of mineral detection using large-scale missions during exploration stages. However, for a more detailed geological analysis, further investigations employing hyperspectral data are recommended due to hyperspectral capabilities to provide contiguous spectral information.

Hyperspectral sensors. In studies characterising geological and mined materials, hyperspectral imaging systems widely used to its ability to record distinct reflectance patterns of materials. These patterns represent contiguous spectral data from minerals in the visible to near-infrared (VNIR) and short-wave infrared (SWIR) ranges. These patterns reflect the minerals' atomic structure and chemical composition. For instance, VNIR images operating in the 0.4–1.0 μm range can map alteration minerals of metal ores such as iron (Fe), copper (Cu), and manganese (Mn). Conversely, SWIR images, which operate in the 0.93–2.5 μm range, are capable of identifying minerals containing OH-groups and carbonates (S. Wang et al., 2022). Due to these capabilities, many studies used hyperspectral imaging for identification of specific minerals such as clay minerals (Lamrani et al., 2021; Murphy et al., 2015), tin-tungsten (Lobo et al., 2021), calcitic and dolomitic carbonate units (Thiele et al., 2021), dolomite, limestone distribution (Kurz et al., 2022), lithium-bearing minerals (Booysen et al., 2022), and ferric iron minerals (Murphy & Monteiro, 2013). However, due to the limited spatial resolution of hyperspectral data, it is often used in conjunction with other sensors that have a higher spatial resolution. This combination allows for more detailed and spatially precise geological studies. For instance, a system combining a Canon EOS 6D DSLR camera and a HySpex SWIR-320 camera was used to map dolomite and limestone distribution in weathered outcrops (Kurz et al., 2022). In a study conducted by Lobo et al. (2021), a detailed mapping and characterisation of Tin-Tungsten deposits were carried out using Specim F×10and F×17hyperspectral cameras, along with a Canon 60D RGB camera. The hyperspectral cameras, F×10and FX17, were particularly notable for their extensive spectral range of 97–1720 nm. This range was divided into 628 spectral bands, each with a Full Width at Half Maximum (FWHM) ranging from 1.34 to 3.48 nm. Furthermore, these cameras boasted a resolution of 1024 pixels per line, ensuring high-definition imaging for the study. This combination of sensors facilitated a comprehensive spatial and spectral analysis of the deposits. Further, the applications are extended to discriminating between ore and waste in a porphyry copper deposit, thereby facilitating efficient extraction processes and indirect characterisation of ore grade (Dalm et al., 2017).

Airborne hyperspectral sensors have played a pivotal role in the detection and characterisation of mining materials. Specifically, they have been crucial in mapping hydrothermal alteration zones, which has significantly contributed to mineral exploration efforts. These sensors provide data that enhances the understanding of mineral compositions and distributions, thereby facilitating more efficient and targeted exploration strategies. The AVIRIS (and subsequently AVIRIS-NG) sensor, mounted on the ER-2 aircraft, is a notable example of such sensors. It provides hyperspectral data with 224 continuous spectral channels covering the wavelength range of 0.38–2.5 μm. With an approximate 10 nm spectral interval and a spatial resolution of 15.5 m × 15.5 m, it has proven effective in detecting and accurately characterising hydrothermal alteration zones (Adep & Ramesh, 2017). Another effective hyperspectral scanner is the ProSpecTIR-VS, flown on a Cessna 206 aircraft. It offers a nominal 5 nm spectral resolution in the 0.4–2.45 μm range and a spatial resolution of 1 m. The thermal imagery analysis from this sensor confirmed strong spatial heterogeneity of surface heat sources and overall higher surface temperatures for acid-sulphate alteration zones (Kruse et al., 2012). In 2022, the NEO HySpex was introduced with 504 spectral channels in the spectral ranges of 0.4–1.0 μm and 1.0–2.5 μm (S. Wang et al., 2022). This sensor was used for detecting and mapping alteration zones in a porphyry mineralisation area. The studies show the use of increased spectral resolution over a short span, from 224 spectral channels in AVIRIS to 504 spectral channels in NEO HySpex, for material characterisation. This progression indicates the continuous advancements in hyperspectral sensing technology and its increasing effectiveness in mineral exploration in mine sites.

Spaceborne hyperspectral imaging has brought about a revolution in the domain of large-scale mineral exploration. It has particularly enhanced the efficiency of early-stage exploration processes. It involves the use of sensors, such as the Hyperion, which offer 242 spectral bands, allowing for detailed analysis of the Earth's surface. The high spectral resolution (10 nm) of these images enables the identification and characterisation of different materials based on their unique spectral signatures. This technology has been instrumental in enhancing geological mapping and early-stage exploration work (Mielke et al., 2016Nair et al., 2020; Sudharsan et al., 2019), as it provides comprehensive data about the mineral composition. Furthermore, the wide swath width of 7.5 km and spatial resolution (30 m) of these sensors allow for large-scale and precise imaging, making hyperspectral imaging an invaluable resource in the field of geology and mineral exploration. The potential of spaceborne hyperspectral imaging continues to be explored, promising exciting advancements in the future (Kumar et al., 2020). emphasised the need for improvements in the signal-to-noise ratio (SNR) of future spaceborne sensors to match the material mapping capabilities of current airborne sensors like AVIRIS. Recent studies have identified PRISMA data as a viable alternative to Hyperion, largely due to its superior SNR (Habashi et al., 2024).

Panchromatic sensors. In the domain of grayscale data capturing, specific camera and lens models are selected for their unique capabilities that cater to the requirements of the task at hand. For ground-based applications, such as the sorting of coal and gangue, the Hikrobot MV-CA050-10 GMGC, a 5-megapixel 23" CMOS GigE Area Scan Camera, is employed. This camera model is favoured for its small exposure time, high resolution, excellent imaging quality, high transmittance, good stability, and manual aperture control. The camera lens used in conjunction is the Hikrobot MVL-MF0828M-8MP, a high-resolution prime fixed focal length 23" 8 mm 8MP FA Lens, which enhances the imaging clarity (Jiang et al., 2021). For airborne applications, the Canon EOS M camera is used in tandem with the Rikola Hyperspectral Imager for capturing overlapping hyperspectral scans of the pit wall. The Canon EOS M camera, along with its lens (EF-M 22 mm f2 STM), is utilised to capture grey-scale images as part of the photogrammetry workflow. The camera positions are determined from an attached GPS device, and the imaging geometry is reconstructed using a SfM and multiview stereo (MVS) workflow (Lorenz et al., 2018). The careful selection of these camera and lens models is pivotal in achieving accurate image recognition and sorting in ground-based applications, and precise reconstruction of surface geometry in airborne applications. Thus, the choice of camera and lens models plays a crucial role in the success of grayscale data capturing tasks, whether they are ground-based or airborne.

Sensor fusion. Numerous studies have validated the effectiveness of an integrated approach, utilising multiple sensors and platforms, in obtaining comprehensive material characteristics across large mine areas. A study by Kokaly et al. (2017) compared the Corescan Hyperspectral Core Imager Mark III, HyMap, and HySpex SWIR – 384, each offering different spectral and spatial resolutions. The study assessed the consistency of mineral information derived from these spectrometers across various datasets, successfully identifying porphyry copper-related alteration and mineralised rock in remote areas. Another study integrated terrestrial and airborne multi-sensor remote sensing techniques for exploration mapping and monitoring, employing ground-based hyperspectral data from Specim AisaFenix and Telops Hyper-Cam LW, as well as UAV-based data from Senop Rikola (Kirsch et al., 2018). This approach demonstrated its ability to map vertical outcrops in a quarry, including sulfide-rich hydrothermal zones. Barton et al. (2021) used a combination of ground and UAV-based hyperspectral imaging using a Headwall Photonics Micro-Hyperspec system, exploring the potential of hyperspectral imaging in conjunction with lidar data for accurate large-scale mineral mapping. Lidar data integration helps in generating spatially registered maps of different mineral types. Further, multiple sensors help in overcoming the limitations and potential sources of error in single sensor-based imaging, such as noise in spectra and the presence of mineral mixtures within pixels. In a recent study conducted by Thiruchittampalam et al. (2024), an RGB sensor (Zenmuse P1) and a multispectral sensor (Micasense Altum PT) were utilised in a UAV to gather textural and spectral data for the characterisation of spoil material in a spoil dump area. The study demonstrated that the higher spatial resolution provided by the RGB sensor, coupled with the higher spectral resolution offered by the multispectral sensor, contributed to a more comprehensive feature set, thereby enhancing the accuracy of classification.

The combination of airborne and spaceborne imaging systems, specifically the Hyperion, AVIRIS, and AVIRIS-NG sensors, and the VNIR-SWIR spectral bands of ASTER data, has also been shown to be effective for mineral exploration and mapping. Kruse et al. (2003) utilised both the Hyperion sensor and the airborne AVIRIS sensor, demonstrating that the combination of these sensors could yield valuable geologic and mineralogic information. Similarly, Kumar et al. (2020) combined the use of AVIRIS-NG hyperspectral data and the VNIR-SWIR spectral bands of ASTER data for lithological mapping. The amalgamation of data from AVIRIS-NG and ASTER facilitated the formulation of an innovative methodology. This methodology integrates spectral enhancement procedures with machine learning protocols to automate lithological mapping. By capitalising on the advantages inherent in both datasets, this approach significantly enhances the precision of lithological categorisation.

The integration of satellite, and airborne sensors has significantly enhanced the efficiency and accuracy of geological and mined material characterisation, particularly in remote and inaccessible areas. A study by Booysen et al. (2019) employed a multiscale remote sensing approach using multiple sensors and cameras, including the Sensefly eBee equipped with a Canon S110 RGB camera, the Aibotix Aibot X6v2 equipped with a Senop Rikola hyperspectral imager, the HyMap-Hyperspectral whiskbroom sensor for aerial hyperspectral imaging, and the ASTER sensor for spaceborne multispectral imaging. Each sensor offered different spectral channels and spatial resolutions, allowing for detailed analysis of targets at various spatial levels. These studies demonstrated the effectiveness of this integrated approach in an area characterised by remote and difficult terrain such as mine area. These findings underscore the potential of a multiple sensors and platform-based remote sensing approach in enhancing material characterisation.

Overview of the review

The process of characterising geological and mined material using image analysis techniques encompasses several steps (Figure 5). The workflow typically begins with preprocessing, which involves preparing the raw data for further analysis by correcting distortions and enhancing image quality. Feature extraction then

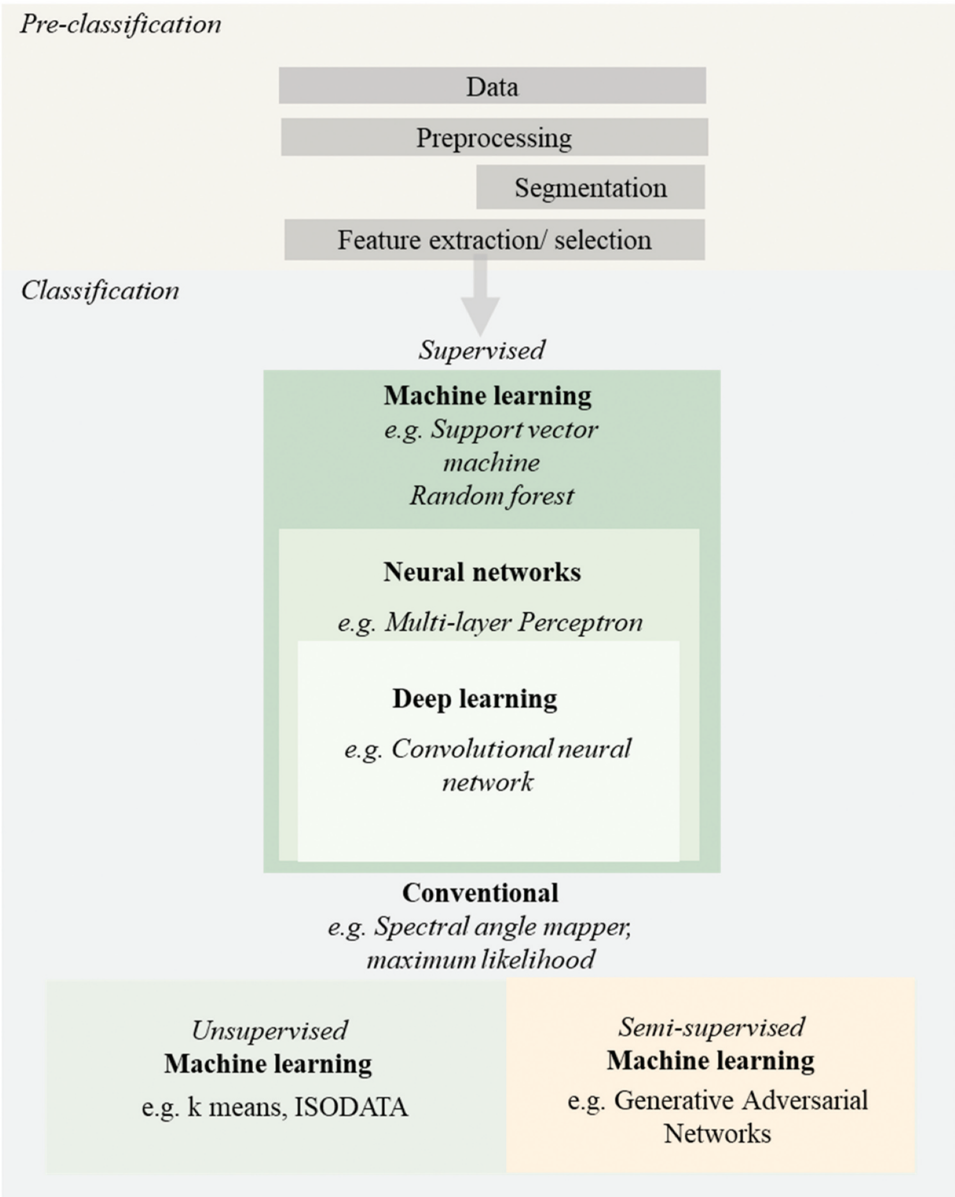

Figure 5. This review evaluates the processes from pre-classification to classification involved in machine learning-based data analysis for geological and mined materials throughout the mining cycle, utilising remote sensing data.

derived to capture local, global, and object-specific information, respectively (W. Fu & Yang, 2022). Feature selection follows, aiming to identify the most relevant features for improving the efficiency and accuracy of subsequent classification tasks. In recent years, machine learning techniques, including supervised, semi-supervised, and unsupervised learning, have been employed to enhance classification performance, complementing conventional methods. Supervised learning relies on labelled data, but its effectiveness is often limited by the availability of such data. Semi-supervised learning, which combines a small amount of labelled data with a larger pool of unlabelled data, has shown promise in improving classification accuracy while reducing the need for extensive manual labelling (Zhixin Zhang et al., 2024). Unsupervised learning, on the other hand, does not require labelled data and is used to discover patterns and structures within the data, although it may not always meet practical application needs (Guo et al., 2022). Advanced techniques like Generative Adversarial Networks (GANs) models have been integrated into semi-supervised frameworks to further enhance feature representation and model robustness, thereby improving the overall performance of image analysis. This review discusses the evolution of geological and mined material characterisation in mining, from preprocessing to classification, over the past two decades throughout the entire mining cycle (i.e. exploration, extraction and waste management).

Machine learning based data analysis for geological and mined materials in the mining cycle

Exploration

Drill core mapping

The rise of machine learning-driven data analysis has significantly transformed the examination of drill cores, transitioning from a subjective and labour-intensive process to a more automated and objective system. Recent studies highlight the considerable promise of integrating various data sources, particularly hyperspectral data with mineralogical information, alongside advanced deep learning techniques. This integration aims to enhance machine learning workflows, improving both efficiency and accuracy while addressing the limitations of existing core logging methods.

For instance, Acosta et al. (2019) demonstrated the effectiveness of combining hyperspectral data with detailed mineral images obtained from scanning electron microscopy-mineral liberation analysis (SEM-MLA). Their methodology included critical preprocessing steps, such as adjusting high-resolution MLA images to align with the spatial resolution of hyperspectral data. By visually coregistering the images based on structural features and mineral compositions, they effectively fused the datasets for classification. They employed machine learning classifiers like Random Forest (RF) and Support Vector Machine (SVM), which are adept at handling high-dimensional data with limited training samples. Their findings indicated that this framework successfully mapped minerals and alteration patterns in drill-core samples, showcasing the potential of data fusion and machine learning in geological analysis.

Similarly, Contreras Contreras et al. (2019) further explored the capabilities of hyperspectral data, focusing on determining different mineral assemblages, structural features, and alteration patterns. Utilising a SisuRock drill core scanner equipped with an AisaFenix VNIR-SWIR hyperspectral sensor, they conducted extensive preprocessing to correct for sensor shifts and lens effects. They employed the Extreme Learning Machine (ELM) technique for classification, which proved to be more efficient than traditional methods like RF, particularly when dealing with less mixed materials. This study highlighted the importance of optimising classification techniques and exploring feature extraction methods to enhance accuracy in mineral mapping tasks.

In another approach, Pane and Sihombing (2021) utilised spectral data from Short-Wavelength Infrared (SWIR) and Thermal Infrared (TIR) to identify mineral features, evaluating various classification methods such as K-Nearest Neighbors (KNN) and Multi-layer Perceptron (MLP). Their findings underscored the effectiveness of SVM and MLP in classifying rock minerals, while also acknowledging limitations such as potential overfitting and challenges in generalising models to different regions. This highlights the ongoing need for refinement in machine learning methods to ensure robust applications in geological research.

Günther et al. (2021) contributed to this discourse by employing high-resolution RGB images of drill cores, addressing preprocessing challenges such as digital depth references and image quality variability. Their use of the Mask R-CNN model demonstrated that even minimal labeled data could yield significant efficiency gains in manual drill core analysis. However, they also identified the need for further evaluation of labelled data selection and the challenges posed by inconsistent image quality. This indicates the necessity of establishing strict guidelines for data acquisition to fully utilise machine learning's potential in geological applications.

Lastly, Abdolmaleki et al. (2022) focused on hyperspectral images of drill core samples from a silver ore deposit. The study utilised ENVI's spectral hourglass workflow, which involved reducing the dimensionality of the hyperspectral data from 256 bands to 40 using a Minimum Noise Function (MNF) transformation. By comparing a supervised deep learning model, ENVI-Net5 architecture, with traditional methods like the Spectral Angle Mapper (SAM) and k-means clustering, they found that the deep learning approach significantly outperformed the others in ore and waste discrimination. However, the study also noted limitations, such as the potential for false positives and the challenges of replicating ideal laboratory conditions in the field. These studies demonstrate the importance of continuous improvement and adaptation of machine learning techniques to ensure their effectiveness in real-world geological scenarios.

In-field geological and mineralogical mapping

In recent years, the integration of machine learning techniques into geological and mineralogical mapping has revolutionised the way data is analysed and interpreted. This section provides a brief overview of these advancements and their implications for the mining field.

For instance, Kruse et al. (2003), centered around the Earth Observing 1 Hyperion Sensor, aimed to evaluate its effectiveness in mineral mapping relative to the established AVIRIS sensor. Key preprocessing steps included atmospheric correction to achieve apparent reflectance, linear transformations to minimise noise, and destriping to address vertical striping in Hyperion data. The classification process employed Minimum Noise Fraction (MNF) transformation to enhance spectral data and identify endmember spectra for mineral mapping. Although the findings indicated that Hyperion could yield comparable mineralogical insights to AVIRIS under optimal conditions, its lower signal-to-noise ratio (SNR) posed limitations on detailed spectral mapping, especially in challenging environments. Kurz et al. (2008) shifted the focus to the integration of lidar and ground-based hyperspectral scanning to improve geological mapping methodologies. This study emphasised the importance of robust data preprocessing, which involved the application of image processing algorithms to extract geological features, registration of hyperspectral images to the lidar coordinate system, and bundle adjustment for precise image orientation and positioning. The classification utilised a maximum likelihood classifier based on the first ten bands of the MNF transform to effectively distinguish geological from non-geological pixels. The results revealed a more nuanced understanding of geological distributions, particularly in limestone and dolomite layers, although challenges such as sensor noise and reflectance correction underscored the need for further refinement. Similarly, Kurz et al. (2009) and Kurz et al. (2013) employed Mixture Tuned Matched Filtering (MTMF) to unmix spectral data, generating thematic images that classify various rock types, such as limestone and dolomite, and quantify dolomitisation and clay content. The study acknowledges limitations, including challenges in semi-automatic feature extraction from lidar data and the impact of factors like shadowing and low signal-to-noise ratios on method effectiveness. Similarly, Kruse et al. (2012) employed minimum noise fraction (MNF) transformation was employed for spectral compression and noise suppression, facilitating effective classification through matched filter (MF) and mixture tuned matched filtering (MTMF) algorithms. The study's findings underscored the capability of HSI to reveal mineral distributions in three dimensions, enhancing exploration and evaluation of geological features. However, limitations arose from the National Elevation Dataset's inadequacies affecting geocorrection accuracy. Further, Okyay et al. (2016) et al. focused on the lower Mississippian Reeds Spring Formation, utilising both ground-based hyperspectral imaging and laboratory reflectance spectroscopy. They applied Spectral Feature Fitting (SFF) and Mixture-tuned Match Filtering (MTMF) for classification, revealing a decrease in tripolite with depth. However, geometric distortions in hyperspectral images posed challenges, suggesting integration with terrestrial LiDAR for enhanced accuracy.

In terms of algorithms, Murphy et al. (2012) evaluated the effectiveness of spectral angle mapper (SAM) and support vector machines (SVMs) for classifying rock types using hyperspectral data from the West Angelas mine in Western Australia. SAM calculates spectral angles for classification, excelling in shadowed areas, while SVMs leverage kernel machine theory for nonlinear classification, showing superior results when training and classification data are from the same population (Murphy et al., 2012). However, SVMs face challenges with independent spectral libraries and are sensitive to illumination changes. Consequently, Xu et al. (2019) investigated hydrothermal alteration minerals associated with gold deposits in the Gulong area of Dayaoshan, China, utilising data from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). The study employs a series of preprocessing steps, including atmospheric correction with the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) and mixed pixel decomposition optimised by genetic algorithms, to address challenges posed by high vegetation cover. Support Vector Machine (SVM) methods, enhanced through ant colony algorithm optimisation, are utilised for accurate extraction of mineral alteration information. The study successfully identifies alteration minerals like pyrite, sericite, and chlorite, which are indicative of gold deposits, despite limitations in areas with dense vegetation. Krupnik and Khan (2020) explored high-resolution hyperspectral imaging spectroscopy for mineral characterisation in two geological settings. Using a Specim SWIR camera, they perform spectral analyses and employ three classification techniques: Spectral Angle Mapper (SAM), Support Vector Machine (SVM), and Neural Network. The SVM classifier demonstrates superior performance in classifying carbonate minerals with 84.4% accuracy, while SAM is more effective for sulfide minerals. Kumar et al. (2020) developed a mapping approach for the Hutti greenstone belt in India, utilising AVIRIS-NG using including machine learning algorithms including Support Vector Machine (SVM), Random Forest (RF), and Linear Discriminant Analysis (LDA), with SVM achieving the highest accuracy of 85.48% and a Kappa Coefficient of 0.83. The study highlighted SVM's robustness against sample size reduction and mislabelling, producing a high-resolution litho-contact map. Sang et al. (2020) introduced a novel high-resolution geological mapping method that combines Unmanned Aerial Vehicle (UAV) technology with a Simple Linear Iterative Clustering-Convolutional Neural Network (SLIC-CNN). By automating traditional geological mapping, this approach minimises extensive fieldwork. High-resolution RGB images captured by a DJI Phantom 4 Pro UAV were pre-processed into 32×32 pixel segments to facilitate effective pattern recognition. The classification integrates CNNs for content recognition and the SLIC algorithm for edge detection, achieving an Area Under the Curve (AUC) of 0.937 and a Kappa coefficient of 0.8523, though further refinement is needed for complex geological features. For lithological boundary mapping, Vasuki et al. (2017) introduced the Interactive Lithological Boundary Detection (ILBD) method, which enhances the efficiency of boundary detection in complex geological images. Utilising the Simple Linear Iterative Clustering (SLIC) superpixel algorithm for initial over-segmentation, the method groups pixels based on color similarity in the CIELAB color space. User input is integral, guiding the segmentation process to refine boundaries and correct subtle color changes. The ILBD method significantly reduces interpretation time by a factor of four while maintaining over 96% similarity in boundary detection, showcasing its potential as a complementary tool to machine learning-based classification methods.

Beyond these studies, analysing the outcomes derived from sensors based on the deployed platforms, Murphy et al. (2014) evaluated short-wave infrared (SWIR) absorption features captured at 10 m using a field-based platform for clay layer mapping at a mine face. They employed Automated Feature Extraction (AFE) for classification, which does not require prior spectral knowledge. They found that direct solar illumination yielded consistent clay absorption patterns, while cloud cover introduced noise, highlighting the need for improved detection methods and appropriate selection of platforms. Gloaguen et al. (2018), in their study on mineral exploration in Europe's crust, integrated multi-sensor remote sensing data, including hyperspectral imaging from satellites, UAS, and ground systems. They indicated that UAS can significantly reduce acquisition costs and enhance data information potential, although challenges related to atmospheric effects and topography still necessitate tailored correction workflows. Further, Lobo et al. (2021) explored the use of hyperspectral imaging for identifying mineral ores from tin-tungsten mine excavation faces. They assessed minerals like cassiterite and wolframite under controlled and simulated conditions, achieving 98% accuracy in the laboratory but only 85% in the field due to challenges like mixed pixels and illumination variations, also indirectly highlight importance of appropriate platform selection to improve accuracy of machine learning-based classification.

Extraction

In-field ore waste differentiation

This section explores the application of machine learning algorithms in the mining sector to distinguish between ore and waste materials in-field, focusing on recent developments. Dalm et al. (2017) assessed the potential of short-wavelength infrared (SWIR) hyperspectral imagery for distinguishing ore and waste in a porphyry copper deposit. The study utilised 43 samples collected from a South American mine, with half used for SWIR imaging and the other for X-ray fluorescence (XRF) analysis. Preprocessing involved calibrating the SWIR data for accurate mineralogical mapping, followed by principal component analysis (PCA) to identify variations in mineral composition. The findings indicated that SWIR hyperspectral imaging could discriminate 58% of samples with sub-economic copper grades, although it did not outperform SWIR point spectrometry due to textural variability and a limited sample size. Pu et al. (2019) focused on coal classification using a CNN with transfer learning, utilising the VGG16 model. A dataset of 240 images (100 for training, 20 for validation per material) was created to train the model. Preprocessing included resizing and normalising images to fit the VGG16 input requirements. The CNN achieved an accuracy of 82.5% on the validation set, demonstrating its effectiveness. However, the study acknowledged limitations due to the small dataset size, suggesting that expanding the image database could enhance performance. Choros et al. (2022) developed a prototype scanning system that combined hyperspectral imaging with neural network classification to identify ore at a gold mine in Western

Australia. The system integrated hyperspectral cameras and a 3D LiDAR to capture detailed scans of the mine face. Data preprocessing involved decomposing hyperspectral images into 5 × 5 spatial patches, essential for training a convolutional neural network (CNN). Two classification methods were employed: the Spectral Angle Mapper (SAM) and the CNN. Both methods achieved good accuracy in distinguishing ore from waste, although the quality of classification was limited by the small training dataset and environmental variations impacting performance. These studies highlight the integration of imaging technologies and machine learning algorithms in mining for effective in-field ore-waste classification, while also pointing out challenges such as dataset size, environmental factors, and textural variability that affect classification accuracy.

Material quality monitoring

Recent advancements in machine learning have significantly improved the material quality analysis irrespective of challenges such as heterogenous nature of mined materials.

In the context of size and shape analysis, study by Weixing W. Wang (2007) presents an image segmentation algorithm tailored for analyzing mineral particles, addressing challenges posed by irregular shapes and rough surfaces. The preprocessing phase enhances image quality through edge strengthening and noise reduction, facilitating effective segmentation. A region-based split-and-merge technique is employed for classification, although limitations such as over-segmentation persist, indicating the need for improved shape analysis and localised threshold determination. Later, a study by Zelin Zhang et al. (2013) investigated the accuracy of parameters in machine vision systems for estimating the size distribution of coarse coal particles, utilising a dataset of 467 anthracitic coal particles from the Tai-Xi coal preparation plant. The research highlights the critical importance of precise particle size representation, employing a backlit system for high-quality image capture and advanced segmentation techniques to mitigate edge detection issues. Among the nine parameters analyzed, the minor axis of the equivalent ellipse (Dminor) and the breadth of the best-fit rectangle (DB) exhibited the highest accuracy ratios of 86.43% and 85.39%, respectively, while other parameters fell below 70% accuracy. Iwaszenko and Nurzynska (2019) proposed a robust segmentation method for delineating rock grains using a five-dimensional intensity feature vector. This vector incorporates pixel grey levels and local curvilinearity assessments. Machine learning classifiers, including k-nearest neighbors (kNN), SVM, and artificial neural networks (ANN), are evaluated, with linear SVM achieving the highest accuracy (up to 89%). Despite promising results, challenges such as false positives and segmentation precision in complex structures remain, indicating the need for further refinement. The research conducted by Nurzynska and Iwaszenko (2020) and Iwaszenko and Smoliński (2021) further focused on enhancing rock grain boundary detection through texture analysis and machine learning techniques. The studies utilise images of rock materials, preprocessing them by creating ground truth masks to delineate grain edges. Various classifiers, including k-Nearest Neighbors (kNN), Random Forest (RF), Decision Trees (DT), Support Vector Machines (SVM), and Multi-Layer Perceptron (MLP), were employed to assess their effectiveness in segmenting grain boundaries. SVM with a Radial Basis Function kernel and MLP demonstrated strong performance, albeit with high computational demands. Furthermore, the studies explored texture feature extraction using first-order, second-order features, and matrices such as the run-length and grey tone difference. The ANN classifier achieved over 75% accuracy, improving to 79% with a multi-texture approach. However, limitations were identified, including challenges in resolving fine grains and diminished accuracy from feature space dimensionality reduction.

Other significant contributions by researchers include determining the lithology and grade of ore. Perez et al. (2012) developed a lithological classification method employing Gabor texture analysis combined with support vector machine (SVM) classification. The approach utilises a dataset of 120 rock images, segmented into 128 sub-images for detailed texture analysis. Gabor filters are applied at multiple spatial scales and orientations, generating a feature vector of 240 features per sub-image. The SVM, utilising a radial basis function (RBF) kernel, achieves over 80% accuracy, outperforming previous methods like Wavelet-PCA (40.83%). However, it primarily focuses on texture features, suggesting future enhancements with colour information. Additionally, Mohapatra (2015) proposes a methodology for automated coal grade characterisation using image processing and machine learning, addressing the limitations of traditional analysis methods. This study employed a Radial Basis Function Neural Network (RBFNN) for classification, which outperformed other classifiers, including Multilayer Perceptron (MLP) and Probabilistic Neural Network (PNN), achieving an average performance accuracy of 90.66% through five-fold cross-validation. The preprocessing for classification involved shifting and contrast enhancement to reduce distortions, and feature selection techniques such as One Way ANOVA were emphasised to enhance classification accuracy.

Patel et al. (2017) aimed to develop an online vision-based technology for iron ore classification, employing a multiclass SVM model with a Gaussian radial basis function (RBF) kernel. Utilising 2200 images captured via a conveyor belt system, the researchers extracted 18 features, including histogram-based color and texture features. The SVM model demonstrated high sensitivity, accuracy, and specificity, outperforming alternative methods such as k-nearest neighbor and Naïve Bayes, despite limitations related to feature similarities among classes. Building upon, Patel et al. (2019a) introduced a support vector machine regression (SVR) model for online quality assessment of iron ores, utilising data from images captured on a conveyor belt. A total of 280 image features were extracted and optimised using a sequential forward floating selection (SFFS) algorithm, enhancing model performance while reducing complexity. The SVR model, employing a radial basis kernel function (RBF), demonstrated a high predictive accuracy with an R^2 value of 0.9402, outperforming other regression models like Gaussian Process Regression (GPR) and Artificial Neural Networks (ANN). However, the model's applicability to diverse mining conditions necessitates recalibration and optimisation due to its tendency to overestimate iron ore grades. Consequently, Patel et al. (2019b) investigated the impact of moisture on SVM performance, utilising both classification and regression models on images of dry and wet ore samples from the Guamine mine in India. This study revealed that dry samples yielded superior model performance compared to wet ones, underscoring the need for tailored feature selection based on sample conditions.

Ore waste differentiation prior to processing

The adoption of machine learning-based data analysis for ore-waste differentiation prior to processing has the potential to enhance both efficiency and accuracy in ore quality assessment and sorting processes prior to processing.

Considering incoporation of traditional machine learning approaches, study by Singh and Rao (2006) explored image processing techniques for distinguishing ferruginous Indian manganese ores. The methodology includes contrast adjustment, conversion to CIELAB color space, and binary image transformation to facilitate classification via the nearest neighbour rule. A Sobel filter is utilised to detect alumina lumps, demonstrating the potential for improved ore quality and sorting. However, the study notes complexities in image characteristics that necessitate further refinement of the processing techniques to enhance accuracy. Dou et al. (2018) employed the Relief-SVM method, which optimises rock picking efficiency under varying surface conditions – dry, wet, and those covered by slime. Using data from Dafeng and Baijigou coal mines, the study processes 16 datasets with 19 features per sample, achieving mean accuracies between 94% and 98% through feature selection and SVM classification. The Relief algorithm enhances classification by evaluating feature importance, allowing for reduced training time with fewer optimal features. Dou et al. (2019) further highlighted that not all features contribute equally, with the H first moment being the most impactful. Desta and Buxton (2020) focused on integrating image and point data to classify ore and waste materials in polymetallic sulphide deposits. Utilising both supervised (K-means) and unsupervised (support vector classification) techniques, the study enhances classification accuracy by fusing data from different spectral regions. Preprocessing steps, including Gaussian filtering and normalisation, ensure data quality. Despite challenges in data integration and feature selection, the study demonstrates the potential of data fusion techniques to improve material classification in high-throughput mining operations. Weidong W. Wang et al. (2021) employed a Support Vector Machine (SVM) for classification, optimising its parameters through K-fold cross-validation. This approach includes converting images to grayscale and applying histogram equalisation, achieving a recognition accuracy of 95.12%. The study highlights the importance of eigenvalues from grayscale means and wavelet coefficients in constructing a mathematical recognition model. Jiang et al. (2021) integrated image processing techniques with a multilayer perceptron (MLP) model, achieving a recognition accuracy of 96.15% and a grasping accuracy of 85% at a conveyor belt speed of 0.4 m/s. The method employs a Gaussian filter for noise reduction and the Reverse Selection Edge Extraction Method (RS-EEM) to eliminate background interference, utilising features derived from the gray level co-occurrence matrix (GLCM) for classification. B. Wang et al. (2022) introduced a novel method for detecting coal content in gangue using image analysis combined with a particle swarm optimisation-support vector machine (PSO-SVM) approach. This method improves upon traditional, labor-intensive techniques by employing high-resolution images captured by a Canon EOS550D camera. The study utilises multiscale image segmentation and various preprocessing techniques to extract relevant features, which are refined using the Pearson correlation coefficient. The PSO algorithm optimises SVM parameters, achieving average relative errors of 9.5% to 10.0% in predicting coal content, offering real-time detection advantages over conventional methods. Huang et al. (2022) aimed to enhance volume prediction accuracy through shape clustering and image analysis. It employs a multiscale edge detection algorithm based on the Gaussian function and Hessian matrix for image segmentation, followed by an improved K-means algorithm for shape classification. This approach significantly reduces average relative errors in volume prediction, notably decreasing gangue particle error from 13.41% to 12.54%. However, limitations include potential errors during segmentation and the influence of abnormal data points on regression results.

Other studies have employed deep learning techniques, where feature extraction is an intrinsic component of the process, for instance, Hong et al. (2017) developed an automatic recognition system using a convolutional neural network (CNN) model based on AlexNet. To address the challenge of limited training data, it employs data enhancement techniques and transfer learning, utilising a dataset of 2012 images from Shanxi, China. The CNN model, fine-tuned for coal and gangue recognition, achieves a recognition rate of 0.96, outperforming traditional neural networks and SVMs. The study acknowledges limitations regarding sample variety and quantity, suggesting future work to expand the dataset for improved generalisability. Li et al. (2019) introduced a hierarchical deep learning framework aimed at improving coal and gangue detection during mining operations. Utilising datasets from three mines in China, the authors employed a Gaussian pyramid principle for preprocessing, enabling multi-level feature extraction. The classification is performed using coal and gangue regional proposal networks (CG-RPN) combined with convolutional neural networks (CNNs), achieving an accuracy of 98.33%, surpassing previous methods by 0.8%. This approach effectively detects multiple objects in a single image, although it highlights the need for model simplification and enhanced multithreading for online applications. Hu et al. (2019) explored the feasibility of multispectral imaging for identifying coal and gangue. It standardises the color space using Gamma correction and extracts features through Histogram of Oriented Gradient (HOG), Local Binary Patterns (LBP), and Haar features. Support Vector Machine (SVM) classifiers, optimised via Grid Search (GS), Genetic Algorithm (GA), and Particle Swarm Optimisation (PSO), are employed for classification. The findings reveal that LBP combined with GS-SVM yields the best classification accuracy. Future work may focus on deep learning algorithms to streamline the identification process, minimising manual preprocessing efforts. Sun et al. (2021) developed a coal and gangue separating robot system utilising a convolutional neural network (CNN) and the CG-YOLO algorithm for high recognition accuracy exceeding 98%. Implemented in a simulated environment, the system optimises layout and performance for real-time operations. These studies demonstrate significant improvements in coal and gangue differentiation, although they face limitations related to image quality, computational intensity, and potential overfitting, suggesting a need for further research to enhance their applicability. Further, these studies highlight the need for further advancements to address regional variability in mined material types and improve system robustness.

Waste management

The development of studies concentrated on detecting and characterising granularity and geotechnical characteristics in mine dump materials through the application of machine learning-based data analysis.

Iwaszenko (2020) aimed to determine the grain size composition of coal mining waste by utilising image processing algorithms. Data was collected from the "Rymer" pile, where rocks were photographed and analyzed in the HSV color space, specifically using the V channel for processing. Various preprocessing filters were tested, with the Median filter yielding the best results. Edge detection was then performed using three algorithms: gradient magnitude, multiscale linear filtering, and the Statistical Dominance Algorithm (SDA). The SDA algorithm proved most effective in delineating grain boundaries, producing long segments and dot-like structures that facilitated segmentation, despite notable over-segmentation compared to manual methods. Limitations included artifacts from poor lighting and challenges in distinguishing true grain edges from shadows and mineral structures. Consequently, Sun et al. (2022) introduced the SLFTIC algorithm, an enhanced superpixel segmentation method aimed at improving the segmentation of coal mine waste rock images. SLFTIC integrates colour, spatial position, and texture information to overcome limitations of traditional segmentation methods, particularly when target and background colors are similar and edges are weak. The algorithm employs a preprocessing step that calculates pixel distances based on these features, utilising a window to assess the convex-concave degree of pixels, which is crucial for accurate clustering. A modified k-means clustering approach is used for classification, focusing on a balanced distance metric that enhances segmentation results for complex textures. The findings indicate that SLFTIC outperforms the traditional SLIC algorithm, showing improvements in undersegmentation error, boundary recall, and compactness, despite a slightly longer processing time due to the additional computations required. Building upon this, Cai et al. (2022) focused on developing a deep learning-based network for detecting and analyzing the granularity distribution of mine dump materials, specifically conglomerate and clay. The researchers created the Conglomerate and Clay Dataset (CCD) through field sampling and image labeling. The model employs random sampling for robust preprocessing and utilises a keypoint-based detection algorithm to localise materials in orthophoto images, avoiding traditional bounding box complexities. The stacked hourglass-type network architecture improves accuracy by leveraging outputs from previous networks. Results demonstrate that this approach outperforms traditional and other deep learning algorithms in granularity detection, achieving minimal error and standard deviation. Taking this further, Thiruchittampalam et al. (2024) focused on enhancing the geotechnical characterisation of coal spoil piles through high-resolution optical and multispectral data combined with machine learning. Conducted at a mine dump site in New South Wales, Australia, UAVs captured imagery using advanced cameras. Preprocessing involved image segmentation using Gaussian blur and Otsu's thresholding to differentiate between background and spoil piles. The classification utilised various machine learning algorithms, emphasising feature selection via the minimum redundancy maximum relevance (mRMR) algorithm. The ensemble (subspace discriminant) algorithm, integrating features from both RGB and multispectral data, achieved an accuracy of 80.2%. The study underscored the importance of incorporating textural, statistical, and structural information while also noting the challenges posed by feature selection and scale on classification outcomes. Together, these studies highlight the potential of machine learning techniques in effectively managing and characterising mining waste, as well as promoting sustainable management practices.

Conclusions

This systematic review underscores the transformative advancements in the application of image analysis for remote sensing data-based geological and mined material characterization over the past two decades. The evolution of image sensors, progressing from basic RGB technologies to sophisticated hyperspectral systems, has significantly enriched our understanding and analysis of geological and mined materials. The integration of multi-sensor data has emerged as a significant technique for geological mapping, enhancing the precision of geological feature interpretation and enabling more accurate assessments in complex environments.

Innovative classification methods have proven effective in mineral identification, although challenges such as sensor noise and mixed spectral signals persist. The incorporation of advanced machine learning models, particularly deep learning frameworks, has revolutionised the extraction phase, facilitating accurate differentiation between ore and gangue. Despite these promising developments, critical limitations remain, particularly in the areas of model simplification, multithreading capabilities, and image segmentation accuracy. Addressing these challenges is essential for optimising systems to enable real-time detection and more effective sorting processes. Furthermore, the progress in waste management through sophisticated algorithms emphasises the importance of feature integration for accurate waste characterisation while also highlighting issues such as over-segmentation that require further refinement.

Overall, the findings of this review advocate for continuous innovation in machine learning-based remote sensing data analysis within the mining sector. By refining methodologies, enhancing sensor capabilities, and optimising algorithms, the industry can improve resource management and promote environmental sustainability, paving the way for a more efficient and responsible future in mining. The ongoing research and development in this field will be crucial to overcoming existing challenges and fully realising the potential of these advanced technologies.

Author contributions

Conceptualisation, Sureka Thiruchittampalam, Simit Raval, Bikram Pratap Banerjee, Nancy F Glenn; Formal analysis, Sureka Thiruchittampalam; Funding acquisition, Simit Raval; Investigation, Sureka Thiruchittampalam; Methodology, Sureka Thiruchittampalam, Simit Raval, Bikram Pratap Banerjee, Nancy F Glenn; Project administration, Simit Raval; Supervision, Simit Raval, Bikram Pratap Banerjee, Nancy F Glenn; Validation, Simit Raval, Bikram Pratap Banerjee, Nancy F Glenn; Visualisation, Sureka Thiruchittampalam; Writing – original draft, Sureka Thiruchittampalam:; and Writing – review & editing, Simit Raval, Bikram Pratap Banerjee, Nancy F Glenn.

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