AI-Powered Automated Detection of Shotcrete Thickness Deficiencies in Underground Mining: A Safety Innovation for the Mining Sector

C. Sanga Quiroz, Doctor [1], A. Sanga Huayhua, Engineering [2], P. Sanga Huayhua, Student [3], Nelson Chambi Quiroz, Master [4]
[1,2,3,4] Universidad Nacional San Agustín, Perú, csanga@unsa.edu.pe, asanga@unsa.edu.pe, psangah@unsa.edu.pe, nchambiq@unsa.edu.pe

Abstract*– The verification of shotcrete thickness in underground mining is a critical safety task that exposes personnel to risks including rock falls and material detachment. This study presents an AI-based methodology for automated thickness verification using computer vision and deep learning. The approach consists of five steps: reference image acquisition, post-application image capture, image alignment and processing with a U-Net convolutional neural network (6-channel input: RGB_pre ‖ RGB_post), 3D thickness calculation, and heat map generation. The model employs early fusion and a composite loss function (Dice + Focal/Tversky) optimized with Adam and early stopping. Results demonstrate that the AI method generates continuous thickness maps identifying underthickness areas with high accuracy, validated by correlation with physical measurements. The analysis reveals that underthickness is predominantly concentrated at the crown/roof, consistent with gravity-induced sagging. The methodology eliminates personnel exposure to risk zones, directly addressing the leading cause of fatal accidents in Peruvian underground mining, where rock falls represent 50% of accidents in 2024. It is concluded that the AI-based methodology is technically viable, operationally effective, and significantly improves safety by removing workers from the line of fire.

Keywords*-- Artificial intelligence, Shotcrete thickness, Underground mining, Computer vision, Mining safety.

I. Introduction

Peru has consolidated its position as one of South America's leading mineral exporters, standing out as one of the world's largest producers of silver, copper, and zinc [1]. This leadership position is supported by vast geological potential, which contributes significantly to the national Gross Domestic Product (GDP) [2]. The mining sector represents a fundamental pillar of the Peruvian economy, generating employment, foreign currency, and regional development. However, mining activity inherently involves complex and high-risk processes, particularly during the underground extraction phase, where operational conditions are extreme and safety is paramount.

The mineral extraction process in underground operations consists of a critical sequence of interdependent stages: drilling and sampling, explosive charging, blasting and ventilation, ore extraction, rock scaling, and finally, ground support (see Figure 1). This last stage is not only crucial for ensuring structural stability of mining workings and operational continuity, but also represents the main barrier between safe working conditions and the occurrence of catastrophic accidents. The lack of adequate support or its sudden failure has direct and serious consequences on the physical integrity of workers. Despite its critical importance, the methodologies for verifying support effectiveness, specifically thickness control of wet-mix shotcrete (sprayed concrete), are still performed manually. This conventional practice involves the physical insertion of cross-shaped gauges into the fresh material; these are mounted on one end of an adjustable gauge holder to reach the upper part of the excavation (crown), as illustrated in Figure 2. This procedure exposes verification personnel to significant risks, including the fall of non-adherent shotcrete fragments or rock falls from the unconsolidated roof, recreating hazardous scenarios during each inspection.



Fig. 1. Mineral extraction cycle.



Fig. 2. Shotcrete calibration.

This is evidenced by tragic incidents recorded in the country. From January to September 2024, seven fatal accidents were reported in the Geomechanics specialty, resulting in eight fatalities, all attributed to rock falls [3]. Statistics from the Mining Safety Institute (ISEM) confirm that rock falls accounted for 50% of accidents in underground mines in 2024, reaffirming a historical trend as the leading cause of fatalities in the sector [4]. Therefore, there is a critical gap between the pressing need to ensure robust ground support and control methods that, paradoxically, increase risk to personnel.

Ground support in underground mining has been extensively studied, with four main types of support systems identified: anchor bolts, mesh, beams, and shotcrete. Each of these systems has been the subject of research aimed at improving their performance, durability, and safety.

Regarding anchor bolt support, crucial investigations have focused on understanding the structural behavior of cable bolts under static shear loads, evaluating various diameters and material strengths. The results demonstrated a direct positive correlation between increased diameter and yield strength of the bolt, and its ultimate load capacity, maximum displacement, and energy absorption capacity, ensuring greater safety and effectiveness in deep mine support [5]. Complementarily, the evaluation of resin-anchored bolts under dynamic loading regimes demonstrated that increasing their diameter and yield strength drastically optimizes their energy absorption capacity, providing a solid technical basis for mitigating the risk of rockbursts [6]. However, it has been noted that the lack of standardization in anchor bolt installation procedures generates significant risks to personnel safety, underscoring the critical importance of following a strict and uniform installation protocol [7].

In the area of mesh support, fundamental studies have compared the behavior of metal mesh (which functions as surface support) with that of bolts (which act as internal reinforcement of the rock mass) within integrated support systems [8]. Figure 3 illustrates a typical mesh support installation in underground mining.

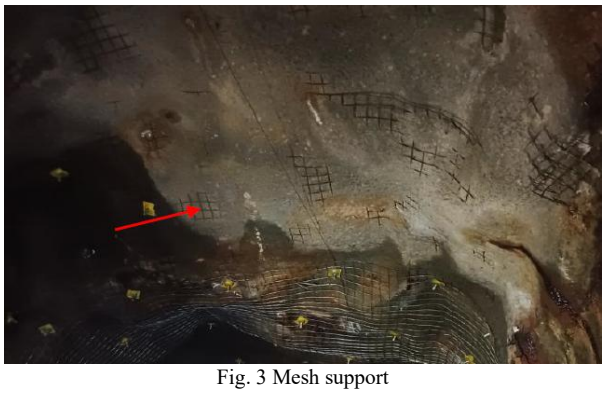


Fig. 3 Mesh support

Regarding beam support, research has demonstrated that high-strength heat-treated lattice girders reduce ground settlements by 7-30% and exert less pressure on the surrounding rock compared to traditional steel arches, while reducing steel consumption by 36% [10]. For effective selection and application of beam support, it is essential to characterize the rock type and have technical usage criteria that allow optimizing progress in mineral extraction [9].

Regarding shotcrete support, wet-mix shotcrete consists of projecting a pre-hydrated concrete mixture onto roofs and walls in underground mining tunnels. Innovative approaches have been developed, including bio-inspired shotcrete that incorporates bacteria through the Microbially Induced Calcium Carbonate Precipitation (MICP) technique to capture CO_2 during application, achieving a mitigation of 0.34 kg CO_2/m^2 [11]. Thin Spray-on Liners (TSL) have been presented as an effective alternative to traditional shotcrete and metal meshes. Figure 4 illustrates the shotcrete spraying system, where (1) compressed air enters to propel the mixture, (2) the additive (accelerator) is injected at the nozzle to accelerate setting, and (3) the shotcrete mixture is projected onto the rock surface. TSLs stand out for their rapid application, high tensile strength, excellent adhesion, and flexibility [12]. A sustainable shotcrete has also been developed from industrial waste and optimized through a hybrid machine learning model, offering a reproducible method for designing mixtures that reduce both costs and environmental impact [13]. Additionally, the use of dry-mix shotcrete has been documented to increase productivity by 55.1% and labor efficiency by 97.9% compared to traditional wet-mix shotcrete [14]. Regarding mechanical performance, research has established key dosages for fiber-reinforced shotcrete and warned of significant discrepancies between standardized testing protocols that can lead to overestimation of actual performance [15].

Beyond traditional support systems, non-destructive technologies have been explored for surface characterization in underground mining. LiDAR (Light Detection and Ranging) has been used for 3D mapping of tunnel geometry and rock mass characterization, enabling remote assessment of excavation profiles and deformation monitoring. Photogrammetry-based approaches have also been applied for rock mass discontinuity mapping and tunnel surface reconstruction. However, these technologies have primarily focused on geometric characterization rather than shotcrete thickness verification. The integration of computer vision and deep learning with these remote sensing techniques remains an open research area, particularly for automated quality control of shotcrete application.

Despite these advances, there is a knowledge gap in the automation of quality control processes for shotcrete application, specifically thickness verification. Current methodologies remain manual, exposing personnel to significant risks and creating a paradoxical situation where the verification of safety measures itself becomes a source of danger. This gap is particularly relevant in the Peruvian mining context, where safety incidents continue to occur at an alarming rate.

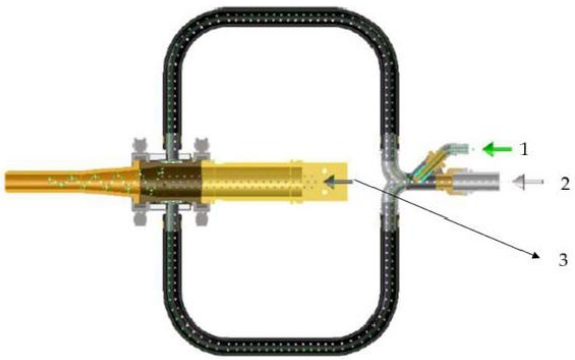


Fig 4 Shotcrete spraying system: (1) compressed air inlet, (2) additive inlet, (3) shotcrete inlet and projection nozzle.

The main motivation for this research arises from the need to protect the physical integrity of workers in underground mining operations. The alarming statistics of fatal accidents attributed to rock falls, which represent 50% of accidents in underground mines in 2024 [4], demand urgent action. The integration of Artificial Intelligence into thickness verification processes offers a promising path to eliminate human exposure in risk zones, reduce operational costs associated with accidents, and improve the overall safety culture in the mining sector. Additionally, the potential for automation aligns with the global trend toward digital transformation and Industry 4.0 in mining.

This study aims to develop and validate an AI-based solution for automating the verification of wet-mix shotcrete thickness in underground mining operations. The proposed solution uses advanced digital image processing techniques to perform precise and remote measurements, eliminating the need for direct human exposure in the risk zone and improving the accuracy and reliability of quality control processes.

The contribution of this research is threefold:

- Technological: While AI and machine learning are not novel in themselves, their application to shotcrete thickness verification in underground mining represents an innovative implementation. This work demonstrates the potential of computer vision to transform a traditional, manual, and hazardous inspection process into a remote and potentially continuous quality control system
- Social: It contributes to the protection of workers' lives by eliminating the need for direct exposure to risk zones during shotcrete thickness verification, directly addressing the leading cause of fatal accidents in the Peruvian mining sector.
- Regional: It provides a solution that can be replicated in other mining operations in Peru and Latin America, contributing to the modernization of the mining sector and strengthening local capabilities in AI applied to mining safety.

The article is structured in five sections. Following this introduction, Section 2 presents the methodology employed for the development of the AI-based solution. Section 3 presents the results of the solution validation. Section 4 discusses the findings. Finally, Section 5 presents the conclusions and recommendations of the study.

II. Methodology

The proposed methodology consists of five sequential steps, designed to automate the verification of wet-mix shotcrete thickness in underground mining operations. The workflow is illustrated in Fig. 5.

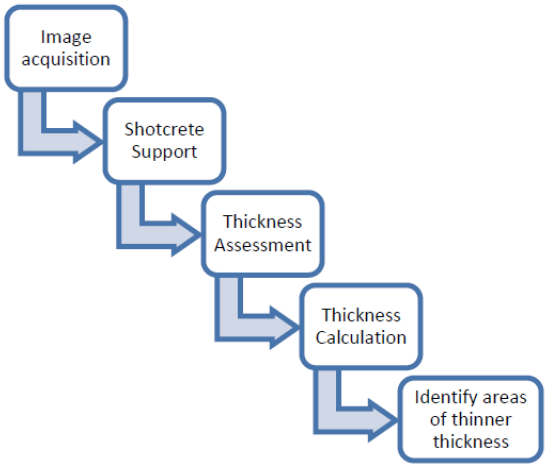


Fig. 5. Proposed methodology for automated shotcrete thickness verification.

2.1. Step 1: Reference Image Acquisition (Pre-Support)

Before starting the shotcrete spraying, high-resolution digital images of the rock surface exposed during the mining operation are systematically captured. This capture is done using cameras with known geometric calibration, mounted on a robotic vehicle to ensure personnel safety by preventing them from entering the risk zone. Photographs are taken from multiple angles and with structured lighting to cover the entire area to be supported (sidewalls and crown), ensuring that textures and irregularities of the rock mass are captured, which will serve as a baseline for later thickness calculations.

Key aspects of this step:

- Camera calibration: Intrinsic and extrinsic parameters are determined to enable metric measurements from images.
- Structured lighting: Controlled illumination minimizes shadows and enhances texture detection.
- Robotic platform: Ensures repeatable positioning and eliminates human exposure to the risk zone.

2.2. Step 2: Shotcrete Application and Post-Image Acquisition

Once the shotcrete application is complete, the image capture protocol is repeated from the same positions and with the same camera parameters used in Step 1. This set of post-projection images documents the final state of the coated surface. Consistency in position and calibration between both imaging campaigns (before and after) is critical to the accuracy of subsequent measurements, as it allows for pixel-by-pixel comparisons.

The shotcrete application follows the support design defined by geomechanics, which specifies the nominal thickness (typically 5–10 cm), the sequence of passes, and the areas to be covered (crown and sidewalls). The application is performed using a robotic shotcrete rig or a manual nozzle, maintaining a perpendicular angle and a distance of 1–2 m from the surface to optimize adhesion and minimize rebound. The accelerator dosage is adjusted according to the mixture design to ensure rapid setting and reduce sagging, particularly on overhead surfaces. The volume of shotcrete applied is controlled by the number of passes and the nozzle displacement speed, ensuring uniform coverage of the designated area.

Key aspects of this step:

- Geometric correspondence: Pre- and post-application images must be perfectly aligned to enable accurate thickness measurement.
- Consistent lighting: Same lighting conditions are maintained to avoid variations in image quality.
- Time efficiency: The capture protocol is designed to minimize time between shotcrete application and verification, enabling rapid quality control.

2.3. Step 3: Image Alignment and Processing with Deep Learning

The paired images (pre- and post-) are processed by a computer vision pipeline. First, a registration algorithm accurately aligns the image pairs to correct for any perspective or position differences. Then, a specifically trained Convolutional Neural Network (CNN) model automatically segments the shotcrete layer in the post images. This model has been pre-trained with an extensive dataset of labeled images to distinguish between shotcrete and rock with high confidence.

To detect shotcrete underthickness by before/after comparison, a U-Net-type convolutional segmentation network is employed. Since the phenomenon is a local change with strong class imbalance, early fusion is adopted: the co-registered image without support and the image with support are stacked as a 6-channel input (RGB_pre ‖ RGB_post). The model learns to segment pixels with insufficient thickness at native resolution.

Training uses pairs annotated by geomechanics experts, with normalization and photometric corrections, in addition to geometric and lighting data augmentation. To mitigate the imbalance, a composite loss (Dice + Focal/Tversky) is optimized with Adam (Adaptive Moment Estimation), a stochastic gradient descent optimizer that adapts the learning rate for each parameter, and early stopping. The output is a calibrated probability map that is thresholded (optimal threshold by F1/Youden) and post-processed (morphology, area filter) to quantify the percentage of surface under the nominal thickness.

Key aspects of this step:

1) Image registration: Feature-based or intensity-based algorithms align pre- and post-application images.
2) U-Net architecture: Encoder-decoder structure with skip connections, proven effective for semantic segmentation in industrial environments.
3) Early fusion: RGB_pre and RGB_post are stacked as 6-channel input, enabling the model to learn the difference between both states.
4) Training dataset: Diverse dataset of underground mining images, annotated by geomechanics experts.
5) Composite loss: Dice + Focal/Tversky loss optimizes segmentation performance despite class imbalance.
6) Post-processing: Morphological operations and area filtering refine the segmentation output.

2.4. Step 4: Three-Dimensional Thickness Calculation and Heat Map Generation

Using data from the calibrated camera and the disparity between the aligned surfaces of the stereoscopic image pairs, a precise 3D point cloud of the surface is reconstructed. The thickness calculation is performed by measuring the perpendicular distance between each point on the shotcrete surface (segmented in Step 3) and the reference rock surface (from Step 1). These values are then projected onto a 3D model of the excavation, generating an intuitive heat map where a color scale (for example, green for adequate thickness, yellow for warning, and red for insufficient thickness) instantly visualizes the thickness distribution across the entire supported area.

Key aspects of this step:

- Stereoscopic reconstruction: Disparity between paired images enables 3D point cloud generation.
- Perpendicular distance measurement: Accurate calculation of thickness at each point on the surface.
- Heat map visualization: Intuitive color coding enables rapid identification of areas with insufficient thickness.

2.5. Step 5: Identifying Critical Zones and Feedback for Re-projection

The system automatically analyzes the generated heat map to identify the specific spatial coordinates of zones where

the measured thickness is below the minimum required by the support design. A detailed report, including the coordinates and the magnitude of the deficit, is immediately sent to the shotcreting team. This report enables precise and selective re-spraying solely in the deficient areas, optimizing material usage and, most importantly, eliminating the need for personnel to enter the area to perform control measurements, thereby completely mitigating exposure to risk.

Key aspects of this step:

1) Automated detection: Algorithm identifies zones below threshold with coordinates and magnitude.
2) Report generation: Detailed report is generated for the application team.
3) Targeted re-application: Material and time are optimized by focusing only on deficient areas.
4) Safety improvement: Human exposure to the risk zone is completely eliminated.

III. Results

This section presents the results of the application of the AI-based methodology for automated shotcrete thickness verification. The results are organized to demonstrate the validation of the proposed method through comparison with manual measurements, the visualization of thickness distribution through heat maps, and the identification of critical areas requiring re-application.

3.1. Manual Verification: The Baseline Problem

In underground mining development headings, verifying the thickness of the applied shotcrete is a high-risk task. Operational personnel must enter the recently supported face (typical advances of ~3 m) to perform manual measurements with a gauge holder. The procedure consists of inserting the gauge into the still-fresh shotcrete, both on the ribs and the back (see Figure 6), until contacting the rock and reading the applied thickness. In practice, the insertion is often deficient: the probe does not enter perpendicularly, it slips or bends, and the reading loses validity; consequently, verification of the required thickness is not guaranteed.



Fig. 6 Shotcrete calibration.

This calibration process places personnel directly in the line of fire (see Figure 7b). The exposure is aggravated by the risk of detachment of fragments with insufficient curing and of loose rocks from the back or upper part (Figure 7a), which represents a constant threat to the worker's integrity. Besides being intrinsically dangerous, this methodology introduces subjectivity and provides discontinuous spatial coverage, leaving critical areas uninspected and compromising the support's effectiveness.



Fig. 7 (a) Shotcrete detachment (b) Shotcrete calibration.

3.2. AI-Based Thickness Assessment

Fig. 8 shows the shotcrete surface immediately after application. It shows the texture of the support (roughness, residual rebound, and nozzle marks), which is difficult to assess with the naked eye due to the lack of objective thickness references and lighting and perspective effects. This image constitutes the input for the artificial intelligence model and the initial reference for detecting irregularities (over/under thickness, porous or segregated areas) and for quantifying the surface homogeneity of the applied material.



Fig. 8 Shotcrete application area.

Fig. 9 shows the processing of the original photograph using artificial intelligence, generating a heat map of shotcrete thickness. This result clearly shows the areas with the greatest and least coverage, represented on the chromatic scale. It is worth noting that the critical areas marked in blue (least thickness) and the areas in red (greatest thickness) coincided with the physical measurements taken in the field, thus validating the reliability of the method. This finding confirms that the proposed technique offers an accurate and non-invasive tool for assessing support in underground mining, optimizing safety and reducing the need for manual inspections.

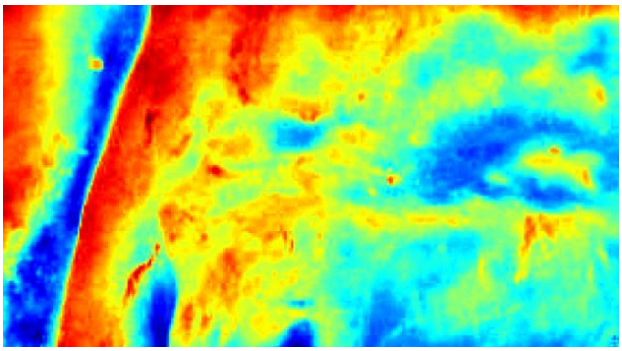


Fig. 9 Thickness measurement with AI.

Color scale legend:

- Blue: Thickest areas.
- Green: Intermediate thickness.
- Yellow: Reduced thickness.
- Red: Critical areas with possible lack of thickness.

3.3. Comparative Analysis: Gable Side (Vertical Surface)

Fig. 10 corresponds to the right gable end of the project. Visual analysis shows small areas with low-magnitude undercoating. This pattern is consistent with a near-normal incidence of the spray on a vertical surface, which improves initial adhesion, reduces rebound, and limits gravity sagging. The results indicate that vertical surfaces exhibit better thickness uniformity compared to overhead surfaces, which is consistent with the physics of shotcrete application.

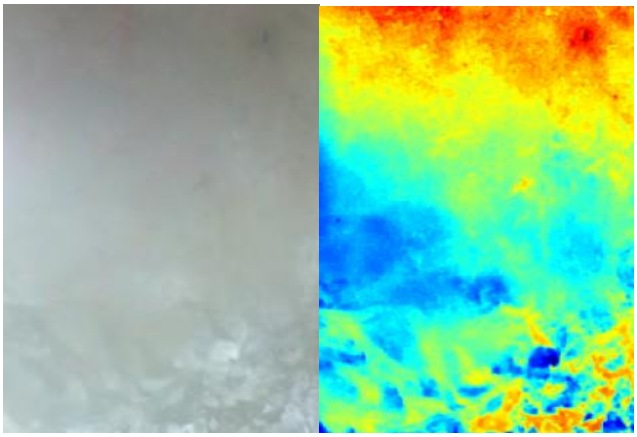


Fig. 10 Gable side with support.

In contrast, a higher prevalence of undercoating is observed on the crown/roof, attributable to application on the intrados and the action of gravity prior to setting, which increases sagging and mortar detachment. This distribution suggests optimizing the nozzle angle and distance, accelerator dosage, and sequence of passes to ensure the nominal thickness and specified homogeneity.

3.4. Comparative Analysis: Crown (Overhead Surface)

At the crown of the work after application of the support and in-situ measurement (see Figure 11), the analysis reveals localized areas with a lack of thickness, especially on intrados surfaces and near fastening elements, where the combination of gravity, rebound, and reduced initial adhesion favors sagging of the material before setting. This pattern reveals spatial heterogeneity in the coating and suggests adjusting the nozzle angle and distance, accelerator dosage, and sequence of passes to ensure the specified nominal thickness.

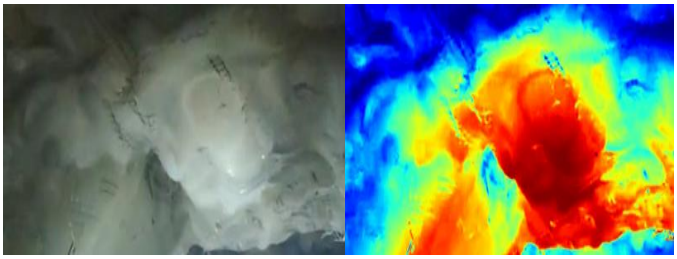


Fig. 11 Crown with support.

3.5. Technical Validation of the AI Model

To detect shotcrete underthickness by before/after comparison, a U-Net-type convolutional segmentation network is employed. Since the phenomenon is a local change with strong class imbalance, early fusion is adopted: the co-registered image without support and the image with support are stacked as a 6-channel input (RGB_pre ‖ RGB_post). The model learns to segment pixels with insufficient thickness at native resolution. Training uses pairs annotated by geomechanics experts, with normalization and photometric corrections, in addition to geometric and lighting data augmentation. To mitigate the imbalance, a composite loss (Dice + Focal/Tversky) is optimized with Adam and early stopping. The output is a calibrated probability map that is thresholded (optimal threshold by F1/Youden) and post-processed (morphology, area filter) to quantify the percentage of surface under the nominal thickness.

3.6. Key Findings

Validation of the AI method: The critical areas identified by the AI model (marked in blue on the heat map) coincided with the physical measurements taken in the field, thus validating the reliability of the method.

Identification of problematic areas: The analysis revealed that overhead surfaces (crown) exhibit a higher prevalence of undercoating compared to vertical surfaces (gable), which is consistent with the physical behavior of shotcrete application.

Operational recommendations: The results suggest optimizing the nozzle angle and distance, accelerator dosage, and sequence of passes to ensure the nominal thickness and specified homogeneity, particularly on overhead surfaces.

Safety improvement: The proposed methodology completely eliminates the need for personnel to enter the risk zone, mitigating the exposure to rock falls and shotcrete detachment.

IV. DISCUSSION

The results obtained in this study demonstrate the technical feasibility and practical value of applying artificial intelligence for automated shotcrete thickness verification in underground mining operations. The AI-based methodology successfully generates continuous thickness maps that enable comprehensive assessment of support quality, overcoming the limitations of manual methods that provide only discontinuous and subjective measurements.

The validation of the AI method is confirmed by the coincidence between the critical areas identified by the model (marked in blue on the heat map) and the physical measurements taken in the field. This finding validates the reliability of the proposed technique and positions it as an accurate and non-invasive tool for assessing support in underground mining. The use of a U-Net architecture with early fusion (6-channel input: RGB_pre ‖ RGB_post) and a composite loss function (Dice + Focal/Tversky) proved effective in detecting underthickness areas despite the strong class imbalance inherent to the problem.

The comparative analysis between manual and AI-based measurements reveals significant advantages of the automated approach. While manual measurements provide discontinuous spot checks that leave critical areas uninspected, the AI method offers continuous coverage of the entire supported surface, ensuring complete identification of underthickness zones. Manual measurements are subjective and operator-dependent, whereas the AI method delivers objective and reproducible results. In terms of safety, the manual procedure requires personnel to enter the risk zone (the line of fire), exposing them to rock falls and shotcrete detachment, while the AI method operates remotely, completely mitigating exposure to these hazards. Furthermore, the AI method reduces inspection time from several hours to minutes, significantly improving operational efficiency.

The spatial analysis of thickness distribution revealed that overhead surfaces (crown) exhibit a higher prevalence of undercoating compared to vertical surfaces (gable). This pattern is consistent with the physics of shotcrete application, where gravity, rebound, and reduced initial adhesion on the intrados favor sagging and material detachment before setting. This finding has direct operational implications, suggesting the need to optimize nozzle angle and distance, accelerator dosage, and the sequence of passes to ensure nominal thickness and specified homogeneity, particularly on overhead surfaces.

For future work, alternative smoothing and clustering methods should be evaluated to improve heat map precision. Simple morphological filters may blur boundaries and lead to over- or under-application in transition zones. Methods such as Gaussian Mixture Models (GMM) or k-means clustering could provide sharper delineation of underthickness areas, enabling more precise re-application strategies.

However, the study presents some limitations. First, the AI model was trained on a specific dataset and may require fine-tuning for different geological conditions, lighting environments, or shotcrete mixtures. Second, the accuracy of the method depends on the quality of image registration and camera calibration, which requires careful execution of the capture protocol. Third, the study did not evaluate the long-term performance of the shotcrete or the evolution of thickness over time under operational conditions.

Despite these limitations, the proposed methodology represents a significant advancement in mining safety and quality control. By eliminating the need for manual inspections in risk zones, the method directly addresses the leading cause of fatal accidents in Peruvian underground mining (rock falls, which represent 50% of accidents in 2024). The technology offers a scalable and replicable solution that can be implemented in other mining operations in Peru and Latin America, contributing to the modernization of the sector and strengthening local capabilities in AI applied to mining safety.

In conclusion, the results confirm that the AI-based methodology is technically viable and operationally promising for shotcrete thickness verification. While the current work represents a proof of concept, the successful implementation of AI in mining applications could significantly reduce personnel exposure to risk zones and contribute to saving lives. Further work is needed to fully automate the process and integrate shotcrete application into the control loop.

IV. CONCLUSIONS

The following conclusions are derived from the application and validation of the AI-based methodology for automated shotcrete thickness verification in underground mining operations.

The heat maps generated by the AI model reveal significant heterogeneity in shotcrete coverage, with localized underthickness concentrated at the crown/roof and, to a lesser extent, in the upper third of the gable end. This pattern is consistent with application on the intrados surface, where pre-set sagging, gravity action, and rebound effects are more pronounced before the material achieves its initial set. The findings confirm that simple visual inspection is insufficient to ensure compliance with the nominal thickness specified by geomechanics, highlighting the need for objective, continuous, and accurate measurement tools such as the proposed AI-based system.

Manual verification with a caliper, if not properly calibrated and standardized in terms of perpendicularity, systematic point selection, repetition, and recording, introduces significant subjectivity and provides only discontinuous spatial coverage. The integration of rigorous calibration protocols with heat map guidance substantially improves the repeatability and traceability of measurements while directing sampling efforts toward areas with the highest probability of underthickness. Most importantly, this approach

eliminates the need for personnel to enter the risk zone, completely removing them from the line of fire and mitigating exposure to rock falls and shotcrete detachment.

The coexistence of underthickness and low early strength at the crown constitutes a critical condition that significantly increases the risk of sagging, delamination, and rockfall, particularly under vibrations and gravity loading. This condition directly elevates the probability of fatal accidents. Therefore, the face should not be cleared or traffic allowed until the identified underthickness areas have been corrected and the minimum early strength and thickness have been verified to conform to the nominal value and design tolerances specified by geomechanics.

The validation of the AI method, confirmed by the coincidence between critical areas identified by the model and physical measurements taken in the field, demonstrates that the proposed technique offers an accurate, non-invasive, and reproducible tool for assessing support quality in underground mining. The use of a U-Net architecture with early fusion (6-channel input: RGB_pre ‖ RGB_post) and a composite loss function (Dice + Focal/Tversky) proved effective in detecting underthickness areas despite the strong class imbalance inherent to the problem, delivering a calibrated probability map that quantifies the percentage of surface under the nominal thickness.

The comparative analysis between manual and AI-based measurements reveals significant advantages of the automated approach, including continuous spatial coverage (vs. discontinuous spot checks), objective and reproducible results (vs. subjective operator-dependent measurements), complete safety (vs. high-risk manual inspections), and reduced inspection time from hours to minutes. These improvements directly address the leading cause of fatal accidents in Peruvian underground mining, where rock falls represent 50% of accidents in 2024.

The findings suggest operational recommendations to optimize shotcrete application, particularly on overhead surfaces: adjusting the nozzle angle and distance to improve adhesion, optimizing the accelerator dosage to reduce sagging, and refining the sequence of passes to ensure uniform thickness distribution. These adjustments would help achieve the nominal thickness and specified homogeneity required by geomechanics design.

Finally, the proposed methodology has the potential to be scalable and replicable in other mining operations in Peru and Latin America, contributing to the modernization of the mining sector and strengthening local capabilities in AI applied to mining safety. However, further validation under diverse geological, lighting, and operational conditions is required before full-scale deployment. The ultimate goal remains the protection of workers' lives by significantly reducing their exposure to the risk zone during shotcrete thickness verification.

REFERENCES

[1] A. Moscoso, “Southern, Antamina y Las Bambas lideran exportaciones mineras de enero a mayo 2025,” Rumbo Minero, Jul. 10, 2025. [Online]. Available: Rumbo Minero – Southern, Antamina y Las Bambas. [Accessed: Aug. 3, 2026].

[2] Banco Central de Reserva del Perú, “Publicaciones,” BCRP. [Online]. Available: BCRP – Publicaciones. [Accessed: Aug. 3, 2026].

[3] Organismo Supervisor de la Inversión en Energía y Minería, Boletín estadístico mensual de accidentes mortales de la mediana y gran minería, Gerencia de Supervisión Minera, Lima, Perú, Sep. 2024. [Online]. Available: OSINERGMIN – Boletín de accidentes mortales, septiembre 2024. [Accessed: Aug. 3, 2026].

[4] R. Alza, “[Exclusivo] ISEM: 50% de accidentes son por caída de rocas en minas subterráneas,” Rumbo Minero, Apr. 9, 2025. [Online]. Available: Rumbo Minero – Accidentes en minería subterránea. [Accessed: Aug. 3, 2026].

[5] F. Tahmasebinia, A. Yang, P. Feghali, and K. Skrzypkowski, “Structural evaluation of cable bolts under static loading,” Applied Sciences, vol. 13, no. 3, Art. no. 1326, Jan. 2023, doi: 10.3390/app13031326.

[6] C. Zhao, Y. Zhang, W. Wu, Z. Zhang, and T. Zhao, “Numerical study on dynamic performance of end-anchored rockbolt under impact loading,” Latin American Journal of Solids and Structures, vol. 18, no. 3, Art. no. e364, 2021, doi: 10.1590/1679-78256458.

[7] C. C. Li, J. Hadjigeorgiou, P. Mikula, G. Knox, B. Darlington, R. Royer, A. Pytlik, and M. Hosp, “Performance of identical rockbolts tested on four dynamic testing rigs employing the direct impact method,” Journal of Rock Mechanics and Geotechnical Engineering, vol. 13, no. 4, pp. 745–754, Aug. 2021, doi: 10.1016/j.jrmge.2021.01.003.

[8] E. Karampinos and J. Hadjigeorgiou, “Quantifying the impact of bolting patterns on the performance of welded wire mesh,” Geotechnical and Geological Engineering, vol. 39, no. 1, pp. 359–376, 2021, doi: 10.1007/s10706-020-01497-x.

[9] C. Qi, J. Liu, X. Shao, X. Yin, W. Li, C. Zhang, Z. Jing, and B. Sun, “Study on mechanical properties of shotcrete lattice girder in a tunnel considering the excavation effect at early-age,” Structures, vol. 62, Art. no. 106196, 2024, doi: 10.1016/j.istruc.2024.106196.

[10] Z. Tan and K. Han, “Experimental study on the application of heat-treated high-strength lattice girder in tunnel engineering,” Symmetry, vol. 11, no. 8, Art. no. 1007, 2019, doi: 10.3390/sym11081007.

[11] Q. Chen, X. Yuan, A. Wu, and Y. Liu, “Enhancing CO_2 mitigation potential and mechanical properties of shotcrete in underground mining utilizing microbially induced calcium carbonate precipitation,” International Journal of Mining Science and Technology, vol. 34, no. 12, pp. 1643–1653, Dec. 2024, doi: 10.1016/j.ijmst.2024.11.007.

[12] H. J. Kim, K. Li, S. Akdag, C. Zhang, J. Oh, P. Jiang, P. T. Spicer, P. B. Zetterlund, and S. Saydam, “Thin spray-on liners (TSLs) as surface support in underground mining: A review,” Construction and Building Materials, vol. 470, Art. no. 140432, Apr. 2025, doi: 10.1016/j.conbuildmat.2025.140432.

[13] X. Wang, L. Feng, B. Han, and Y. Hu, “Preparation, mechanical properties, and machine learning modeling of solid waste based wet shotcrete based on laboratory experiments,” Environmental Technology & Innovation, vol. 38, Art. no. 104187, May 2025, doi: 10.1016/j.eti.2025.104187.

[14] X. Li, H. Zhu, W. Jing, and G. Cheng, “Comparison and analysis of dry mixed mortar and traditional shotcrete and equipment development scheme,” IOP Conference Series: Earth and Environmental Science, vol. 643, Art. no. 012077, 2021, doi: 10.1088/1755-1315/643/1/012077.

[15] V. M. de A. Monteiro and F. de A. Silva, “On the design of the fiber reinforced shotcrete applied as primary rock support in the Cuiabá underground mining excavations: A case study,” Case Studies in Construction Materials, vol. 15, Art. no. e00784, Dec. 2021, doi: 10.1016/j.cscm.2021.e00784.

[16] M. K. Mensah, K. Mensah-Darkwa, C. Drebenstedt, B. V. Annam, and E. K. Armah, “Occupational respirable mine dust and diesel particulate matter hazard assessment in an underground gold mine in Ghana,” Journal of Health & Pollution, vol. 10, no. 25, Art. no. 200305, 2020, doi: 10.5696/2156-9614-10.25.200305.