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AI-Augmented Visual Inspections in Mining and Heavy Industry

Agim Takon

Novation Ltd, Canada

Abstract

AI-enhanced visual inspection solutions are rapidly changing the operational process of mining and heavy industries in terms of safety, reliability, and efficiency. Through a combination of artificial intelligence and computer vision systems, these systems can be used to automatically detect defects, wear and anomalies in complex industrial property and infrastructure. In contrast to the labor-intensive and manual-based inspections, the AI-driven solutions can also be used to provide scalable, real-time, and consistent inspection of hazardous and inaccessible areas, using high-resolution drone, fixed camera, and robot-platform-based imagery. Advanced learning models are used to increase accuracy by recognition of patterns and anomaly detection to aid predictive maintenance and minimize unplanned downtimes. Decision-making is also enhanced with the introduction of AI-enhanced visual inspections because it provides the outputs of the inspections with the help of the asset management and maintenance systems. In spite of the associated data quality, environmental variability and system integration issues, AI-led visual inspection systems present a viable opportunity of safer operations, streamlined resource use and more resilient operations in heavy industrial and mining industries.

Keywords: AI-augmented inspection; computer vision; mining industry; heavy industry; visual analytics; predictive maintenance; industrial safety

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INTRODUCTION TO AI-AUGMENTED VISUAL INSPECTION

AI-enhanced visual inspection is a drastic change in the process of asset monitoring, evaluation, and maintenance in the mining and heavy industries. Conventional on-site scrutinies in these industries are highly dependent on manual checks and evaluation as well as periodic closings, these are normally restricted by the risky nature of the working conditions, poor visibility, and fatigue. With the incorporation of artificial intelligence, specifically computer vision, deep learning, and smart data management, people will be able to inspect and monitor critical equipment, infrastructure, and workspaces continuously, which is scalable and allows people to make more accurate decisions due to increased situational awareness (Santos et al., 2023).

Visual inspection is an integral criterion in mining and heavy industrial processes of identifying structural degradation, surface defects, misalignments and unsafe environmental conditions. AI systems have the capacity to analyze big amounts of visual data of cameras, drones, robotic platforms, and wearable devices to detect anomalies, which can be subtle or not detectable by human inspectors. This capability directly supports occupational safety objectives by reducing human exposure to high-risk zones and enabling early hazard identification (Bęś et al., 2025; Yousefi et al., 2025). Recent advances in smart vision-enabled personal protective equipment, such as AI-integrated safety helmets, further demonstrate how visual intelligence can be embedded directly into industrial workflows (Merchán-Cruz et al., 2025).

Corresponding Author: Agim Takon. Novation Ltd, Canada, Email: atakon2000@gmail.com

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Beyond perception, AI-augmented visual inspection systems increasingly incorporate knowledge-driven and trust-aware layers that contextualize visual findings within operational, safety, and compliance frameworks. These systems combine visual analytics with intelligent data orchestration, explainability mechanisms, and human-in-the-loop oversight to ensure reliability and accountability in safety-critical environments (Komaragiri, 2024; Paleti, 2023; Martino et al., 2025). When coupled with robotic inspection and teleoperation platforms, AI-driven vision extends inspection capabilities into confined, unstable, or hazardous locations that are otherwise inaccessible (Khedr et al., 2025; Haq et al., 2025).

AI-augmented visual inspection forms a foundational component of intelligent industrial safety and asset management strategies. By unifying advanced sensing, autonomous perception, and adaptive decision support, it establishes a pathway toward safer, more resilient, and more efficient mining and heavy industry operations, while maintaining essential human oversight through structured AI-augmented methodologies (Anthuvan et al., 2025).

Operational Challenges in Mining and Heavy Industry Environments

Bubbles Mining and heavy industry The operational environments are some of the most challenging to the visual inspection system. These are extreme environments of physical, environmental and organizational constraints which directly impact on the reliability, scalability and safety of the inspection activities. These issues are also critical to the contextualization of the importance of AI-enhanced visual inspection solutions.

Environmental harshness is also one of the major challenges. The targets of inspection are usually in dusty, wet, vibrating or dark environments that highly undermine the image clarity and sensor functionality. Occlusions, non-uniform light, and particles that frequently occur in underground mining, offshore platforms, and steel plants complicate the pipelines of conventional computer vision technology and require powerful AI-enhanced perception models that can perform adaptive filtering and tolerate noise (Santos et al., 2023; Bęset et al., 2025).

A second critical issue is one of equipment magnitude, complexity and accessibility. Haul trucks, crushers, conveyors, drilling rigs, and pressure vessels are large industrial assets that are complex to operate and are often in continuous operation. The safety risks and loss of productivity that are presented by manual inspections normally involve shutdowns, scaffoldings, or confined-space access. The exact positioning and calibration of the robotic/drone-based inspection platforms continue to be challenging even in limited or GPS-denied spaces, regardless of the dynamic operating conditions (Khedr et al., 2025; Haq et al., 2025).

The limitations on human safety and workforce also add to the operational challenges. Mining and heavy industry are also some of the most perilous locations where occupational accidents take place; as inspectors deal with falling items, respiratory gases, moving equipment, and unstable surface. Qualified inspectors are also unavailable and their evaluations may be subjective, tiredness prone, and inter-shift, inter-site. AI-based enhanced inspection methods should also lower the direct human interaction but help the inspectors with decision support and not process automation (Yousefi et al., 2025; Merchán-Cruz et al., 2025).

Another critical challenge is data heterogeneity and reliability. Visual inspection data in industrial contexts are collected from diverse sources, including fixed cameras, drones, robotic platforms, wearable devices, and smart helmets. These data streams vary widely in resolution, frame rate, viewpoint, and metadata quality, making integration and standardization difficult. Inconsistent labeling practices and limited availability of failure examples further hinder supervised model training and validation (Komaragiri, 2024; Anthuvan et al., 2025).

Finally, trust, compliance, and explainability constraints influence operational adoption. Industrial stakeholders require inspection outputs that are auditable, explainable, and aligned with safety and regulatory frameworks. Black-box AI predictions without traceable reasoning can undermine confidence, particularly in safety-critical decisions such as structural integrity assessments or shutdown triggers. Multi-layer trust and governance mechanisms are therefore necessary to ensure that AI-augmented inspections align with operational risk management practices (Paleti, 2023; Martino et al., 2025).

Collectively, these operational challenges underscore why conventional visual inspection approaches struggle to scale in mining and heavy industry. They also explain the growing interest in AI-augmented inspection frameworks that combine advanced perception, robotics, human-in-the-loop oversight, and trust-aware system design to operate reliably within these high-risk environments.

Computer Vision and Deep Learning Techniques for Defect Detection

AI-augmented visual inspection in mining and heavy industry relies heavily on advances in computer vision and deep learning to automatically identify defects, hazardous conditions, and early indicators of equipment failure under harsh operational environments. These environments are characterized by poor lighting, dust, vibration, occlusion, and highly variable surface textures, which make traditional rule-based image processing approaches insufficient. Modern AI systems instead employ data-driven models capable of learning robust visual representations directly from industrial imagery and video streams (Santos et al., 2023; Bęś et al., 2025).

The core of the majority of defect detection pipelines is based on Convolutional Neural Networks (CNNs), which allow identifying cracks, corrosion, spalling, and misaligned belts, structural deformations, and corrosion in assets (conveyor, haul truck, crushers, pipelines, and underground supports) by default. ResNet, EfficientNet, and YOLO variants are also popular since they have been able to balance both the accuracy of detection and the performance in real-time, which is essential in operational decision-making in safety-related environments (Santos et al., 2023; Yousefi et al., 2025). Semantic and instance segmentation models (e.g., U-Net, Mask R-CNN) can be applied to fine-grained inspections, which allow accurately locating defect boundaries to aid quantitative severity measurements, instead of fault binary classification.

Anomaly detection methods based on deep learning are being actively used in instances where the labelled defect data are limited, which is a widespread issue with the mining

Table 1: Operational Challenges and Their Implications

Challenge Category	*Description*	*Operational Impact*	*Implications for AI-Augmented Visual Inspection*
Harsh Environmental Conditions	Dust, low visibility, vibration, extreme temperatures, moisture	Reduced image quality and sensor reliability	Requires robust computer vision models and adaptive preprocessing (Santos et al., 2023; Bęś et al., 2025)
Asset Scale and Accessibility	Large, complex, and continuously operating equipment	Difficult and risky manual inspections; downtime costs	Drives use of drones, robotics, and teleoperated systems (Khedr et al., 2025)
Worker Safety Risks	Exposure to hazardous zones and confined spaces	High injury and fatality rates; inspection delays	Supports remote and wearable AI-assisted inspection tools (Yousefi et al., 2025; Merchán-Cruz et al., 2025)
Data Heterogeneity	Diverse sensors, platforms, and data formats	Integration and consistency challenges	Necessitates intelligent data management and fusion frameworks (Komaragiri, 2024)
Trust and Compliance Requirements	Need for explainable, auditable decisions	Resistance to black-box AI systems	Encourages explainable AI and risk-aware inspection architectures (Paleti, 2023; Martino et al., 2025)

activity. The variational autoencoders, autoencoder, and self-supervised learning models are trained on a representation of the normal equipment appearance baseline and indicate deviations that can be an indicator of the emerging faults or unsafe environments (Komaragiri, 2024). The methods are especially useful in cases of early defect detection, where visual variations are not much pronounced and cannot be easily spotted by human inspectors.

The latest systems combine vision models and spatial awareness and contextual intelligence in order to boost the reliability of inspections. Vision-based simultaneous localization and mapping (VSLAM) allows inspection platforms, including drones, autonomous vehicles, and smart safety helmets, to have spatial consistency in the process of scanning both large and small industrial spaces (Merchán-Cruz et al., 2025). The georelationship of the identified defects to space enables tracing of the defects through time, and the correlation of the detected defects with the asset history, enhancing longitudinal tracking and maintenance scheduling.

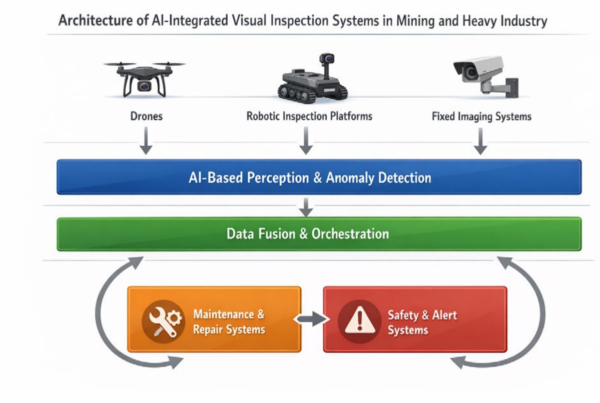

Fig 1: This figure illustrates the high-level architecture of an AI-integrated visual inspection system for mining and heavy industrial environments. Multimodal visual data are acquired through drones, robotic inspection platforms, and fixed imaging systems, and transmitted to a centralized AI analytics layer for perception and anomaly detection. Outputs are integrated through a data fusion and orchestration layer, enabling closed-loop feedback to maintenance, repair, and safety decision-support systems for proactive risk mitigation and operational optimization.

It is also important to note that human-in-the-loop and explainable AI processes are pivotal to determine defects in high-risk industries. Explainability, including saliency maps and attention visualization, enables engineers to check AI decisions and develop functional trust, whereas expert feedback loops constantly improve the performance of the model (Anthuvan et al., 2025; Martino et al., 2025). Trust-layer frameworks further support governance by ensuring that visual inspection outputs comply with safety, audit, and risk management requirements (Paleti, 2023).

ummarizes key computer vision and deep learning techniques used for defect detection in mining and heavy industry, highlighting their typical applications and operational advantages.

When combined with robotic platforms and teleoperated systems, vision-based defect detection extends inspection capabilities into hazardous or inaccessible zones, significantly reducing human exposure to risk (Khedr et al., 2025; Haq et al., 2025). Overall, computer vision and deep learning provide the technical backbone for scalable, accurate, and safety-oriented visual inspection systems, enabling a transition from reactive inspections toward predictive and intelligence-driven asset management in mining and heavy industry.

Integration of AI with Drones, Robotics, and

Table 2: Computer Vision and Deep Learning Techniques for Defect Detection in Mining and Heavy Industry

Technique Category	*Representative Models / Methods*	*Primary Inspection Targets*	*Key Advantages*	*Limitations*
Object Detection	YOLO, Faster R-CNN, SSD	Cracks, loose components, surface damage	Real-time detection, scalable deployment	Requires labeled datasets
Image Segmentation	U-Net, Mask R-CNN	Corrosion, spalling, material loss	Precise defect localization and sizing	Higher computational cost
Anomaly Detection	Autoencoders, VAEs, self-supervised models	Early-stage faults, unknown defects	Minimal labeling requirements	Lower interpretability
VSLAM-Enabled Vision	Visual SLAM, sensor-fused perception	Large-scale infrastructure, confined spaces	Spatial consistency and defect tracking	Sensor calibration complexity
Explainable Vision AI	Attention maps, saliency analysis	Safety-critical inspections	Improved trust and human validation	Added system complexity

Fixed Imaging Systems

The integration of artificial intelligence with drones, robotic platforms, and fixed imaging systems forms the technical backbone of AI-augmented visual inspections in mining and heavy industry. These environments are characterized by large-scale assets, harsh operating conditions, and elevated safety risks, making autonomous and semi-autonomous inspection systems particularly valuable. AI enables these heterogeneous sensing platforms to move beyond passive data capture toward active perception, reasoning, and decision support (Santos et al., 2023).

AI-enabled drones are increasingly deployed for aerial inspection of open-pit mines, tailings dams, conveyor corridors, and high-rise industrial structures. Equipped with computer vision and deep learning models, drones can autonomously detect surface cracks, material deformation, corrosion, and structural misalignment in real time. Their ability to integrate visual data with geospatial mapping allows rapid coverage of inaccessible or hazardous zones while reducing human exposure to risk (Bęś et al., 2025; Yousefi et al., 2025). AI further enhances drone operations through adaptive flight planning, where models dynamically adjust inspection paths based on detected anomalies or environmental constraints.

Robotic inspection systems, including ground robots, climbing robots, and articulated manipulators, complement aerial platforms by enabling close-range, high-precision visual analysis. AI-driven perception systems support object recognition, defect classification, and spatial localization under low visibility or variable lighting conditions. In underground mines and confined industrial spaces, teleoperated and semi-autonomous robots leverage AI for navigation, obstacle avoidance, and situational awareness, reducing cognitive load on human operators (Khedr et al., 2025). Advances in AI-enhanced metrology and sensor fusion further improve robotic positioning accuracy, ensuring consistent visual measurements across inspection cycles (Haq et al., 2025).

Fixed imaging systems, such as mounted cameras, thermal sensors, and smart safety helmets, provide continuous and longitudinal monitoring of critical assets. When integrated with AI pipelines, these systems enable persistent anomaly detection and trend analysis, supporting predictive maintenance strategies. Vision-based simultaneous localization and mapping (VSLAM) techniques embedded in wearable or fixed systems enhance spatial context, allowing detected defects to be accurately referenced over time (Merchán-Cruz et al., 2025). These fixed installations often serve as anchor points for data fusion, aggregating visual streams from mobile platforms into centralized analytics frameworks (Komaragiri, 2024).

At the system level, AI orchestration layers coordinate data flows across drones, robots, and fixed sensors, ensuring interoperability and governance. Knowledge-driven and trust-layer architectures are increasingly adopted to support

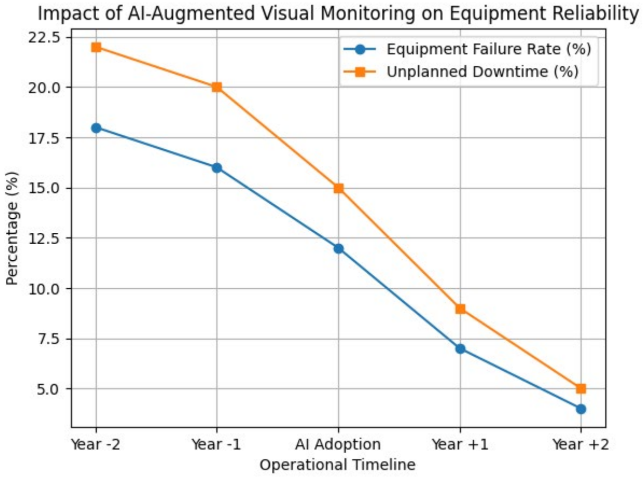

Fig 2: Illustrative comparison of equipment failure rates and unplanned downtime before and after the adoption of AI-augmented real-time visual monitoring and predictive maintenance systems in mining and heavy industry operations.

Table 3: AI-Integrated Inspection Platforms in Mining and Heavy Industry

Platform Type	*Primary AI Functions*	*Typical Deployment Areas*	*Key Safety and Operational Benefits*
Drones (UAVs)	Object detection, surface defect classification, autonomous navigation	Open-pit mines, tailings dams, elevated structures	Rapid area coverage, reduced human exposure, real-time situational awareness
Robotic Systems	Visual perception, sensor fusion, teleoperation assistance, defect localization	Underground tunnels, confined industrial spaces, hazardous zones	High-precision inspections, operation in extreme conditions, operator risk reduction
Fixed Imaging Systems	Continuous monitoring, anomaly detection, trend analysis	Conveyor belts, processing plants, structural supports	Persistent surveillance, early fault detection, predictive maintenance support
Integrated AI Orchestration Layer	Data fusion, explainability, compliance monitoring, decision support	Central control rooms and enterprise systems	Improved interoperability, auditability, and informed maintenance decisions

Table 4: AI-Driven Real-Time Monitoring and Predictive Maintenance Use Cases

Application Area	*AI Visual Inspection Function*	*Integrated Technologies*	*Operational Impact*
Conveyor and Haulage Systems	Detection of belt wear, misalignment, and spillage	Fixed cameras, deep CNNs, edge AI	Reduced unplanned stoppages and maintenance costs
Heavy Machinery (Excavators, Crushers)	Identification of cracks, corrosion, and abnormal vibration indicators	Vision–sensor fusion, predictive analytics	Early fault detection and extended equipment lifespan
Structural Assets (Tunnels, Supports)	Continuous monitoring of deformation and surface defects	Drones, SLAM-enabled vision systems	Improved structural integrity assurance and safety
Robotic and Autonomous Platforms	Visual feedback for condition-based task execution	AI vision, teleoperation control	Safer inspections in hazardous environments
Wearable Inspection Systems	Real-time hazard and defect recognition	Smart helmets, VSLAM, human-in-the-loop AI	Enhanced worker safety and maintenance data quality

explainability, compliance, and human-in-the-loop oversight, which are essential in safety-critical industrial domains (Paleti, 2023; Martino et al., 2025). Such architectures allow inspection insights to be contextualized within operational workflows, enabling timely and defensible decision-making (Santos et al., 2023; Anthuvan et al., 2025).

This integrated ecosystem demonstrates how AI transforms disparate visual inspection tools into coordinated, intelligent systems capable of enhancing safety, efficiency, and reliability across mining and heavy industrial operations (Bęś et al., 2025; Yousefi et al., 2025; Santos et al., 2023).

Real-Time Monitoring and Predictive Maintenance Applications

AI-augmented visual inspection systems play a central role in enabling real-time monitoring and predictive maintenance across mining and heavy industrial operations. By continuously analyzing visual data streams from fixed cameras, mobile robots, drones, and wearable vision systems, these solutions transform traditionally reactive maintenance practices into proactive, condition-based strategies.

In real-time monitoring contexts, computer vision models detect surface defects, structural deformations, corrosion, abnormal wear patterns, and operational anomalies as they emerge. These systems operate at the edge or within hybrid cloud–edge architectures to ensure low-latency decision-making in harsh and safety-critical environments

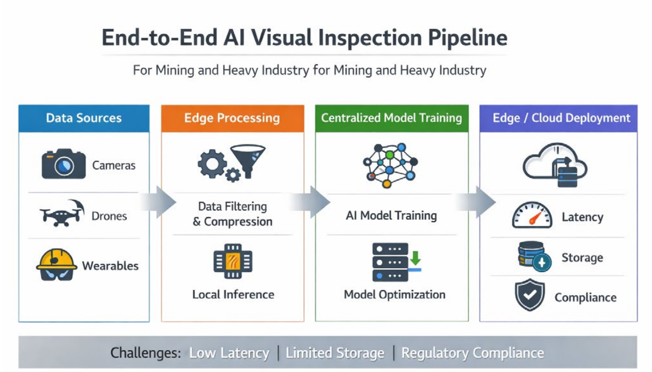

Fig 3: This figure presents an end-to-end AI-augmented visual inspection pipeline for mining and heavy industry, highlighting the flow from distributed visual data acquisition to edge preprocessing, centralized model training, and constrained edge/cloud deployment under latency, storage, and regulatory compliance requirements.

Table 5: Key Constraints Across the AI Visual Inspection Lifecycle

Lifecycle Stage	*Primary Constraint*	*Impact on Operations*	*Representative Mitigation Approaches*
Data Acquisition	Environmental noise and variability	Reduced image quality and detection accuracy	Sensor fusion, adaptive imaging, edge filtering (Bęś et al., 2025)
Data Management	High data volume and governance requirements	Storage overload and compliance risks	AI-driven data orchestration, trust layers (Komaragiri, 2024; Paleti, 2023)
Model Training	Limited labeled safety-critical events	Poor generalization and class imbalance	Human-in-the-loop labeling, transfer learning (Anthuvan et al., 2025)
Deployment	Edge compute and connectivity limitations	Latency and reduced real-time reliability	Model compression, adaptive calibration (Haq et al., 2025; Khedr et al., 2025)

(Santos et al., 2023). When integrated with autonomous or teleoperated robotic platforms, AI vision enables persistent inspection in hazardous zones that are inaccessible or unsafe for human workers, improving both operational continuity and workforce safety (Khedr et al., 2025; Haq et al., 2025).

Predictive maintenance is achieved by fusing visual inspection outputs with historical maintenance records, sensor telemetry, and operational logs. Deep learning models identify degradation trends and correlate visual defect progression with failure modes, allowing maintenance teams to forecast component lifespan and schedule interventions before catastrophic breakdowns occur (Komaragiri, 2024). Knowledge-driven AI frameworks further enhance these capabilities by embedding domain expertise and explainability layers, ensuring that predictions are interpretable and actionable by engineers and decision-makers (Martino et al., 2025; Paleti, 2023).

Wearable and embedded vision systems, such as smart safety helmets equipped with VSLAM-enabled cameras, extend real-time monitoring to human-centric inspections. These systems support continuous situational awareness, automatic hazard recognition, and visual documentation of asset conditions during routine operations, feeding predictive maintenance pipelines with high-fidelity contextual data (Merchán-Cruz et al., 2025). Such AI-driven monitoring directly contributes to reduced downtime, optimized asset utilization, and enhanced occupational safety outcomes in mining and heavy industry settings (Bęś et al., 2025; Yousefi et al., 2025).

Overall, AI-augmented real-time monitoring and predictive maintenance applications represent a foundational shift toward intelligent, self-aware industrial systems. By combining continuous visual perception with advanced analytics and knowledge-driven frameworks, mining and heavy industries achieve higher reliability, safety, and operational efficiency while minimizing risk and lifecycle costs (Santos et al., 2023; Komaragiri, 2024; Martino et al., 2025).

Data Management, Model Training, and Deployment Constraints

AI-augmented visual inspection systems in mining and heavy industry are fundamentally constrained by how data are acquired, governed, trained upon, and operationalized in harsh, safety-critical environments. Unlike controlled manufacturing settings, mining operations generate heterogeneous, high-noise visual data from drones, fixed cameras, robotic platforms, and wearable systems such as smart helmets. These data streams vary widely in resolution, illumination, viewpoint, and environmental interference (dust, vibration, low visibility), creating significant challenges for scalable data management pipelines (Bęś et al., 2025; Merchán-Cruz et al., 2025).

From a data management perspective, volume, velocity, and veracity are the dominant constraints. Continuous video feeds and high-frequency image capture rapidly exceed on-site storage capacities, necessitating edge filtering, compression, and selective retention strategies. Intelligent data orchestration layers often supported by AI-driven service operating systems—are required to prioritize safety-critical events, manage metadata, and synchronize visual data with sensor, telemetry, and maintenance logs (Komaragiri, 2024; Santos et al., 2023). In regulated industrial environments, governance mechanisms such as auditability, access control, and compliance monitoring further complicate data lifecycle management, particularly when visual data contain sensitive operational or workforce information (Paleti, 2023).

Model training introduces additional constraints due to label scarcity, class imbalance, and contextual dependency. Safety-relevant defects (e.g., structural fractures, belt misalignment, unsafe worker postures) occur infrequently, limiting the availability of representative labeled samples. Human-in-the-loop strategies are therefore essential to iteratively refine annotations, validate edge cases, and reduce model drift over time (Anthuvan et al., 2025). Moreover, models trained in one mine or industrial site often fail to generalize due to site-specific geology, equipment configurations, and operational practices, increasing the need for transfer learning and continual adaptation (Yousefi et al., 2025).

Deployment constraints are most pronounced at the edge, where latency, connectivity, and computational limitations intersect with safety requirements. Real-time visual inspection demands low-latency inference on embedded devices mounted on mobile robots, drones, or wearable systems, often operating with intermittent network access.

This restricts model complexity and necessitates optimized architectures, sensor fusion, and adaptive calibration to maintain accuracy under dynamic conditions (Haq et al., 2025; Khedr et al., 2025). Additionally, explainability and trustworthiness remain critical deployment considerations, as inspection outputs frequently inform high-risk decisions such as equipment shutdowns or personnel evacuation (Martino et al., 2025).

Overall, effective AI-augmented visual inspection in mining and heavy industry depends not solely on algorithmic sophistication, but on robust data governance, adaptive training workflows, and deployment architectures that explicitly account for environmental uncertainty, safety accountability, and operational scalability (Santos et al., 2023; Yousefi et al., 2025).

CONCLUSION

Mining and heavy industry Visual inspections augmented with AI are already changing the industry, as they help inspect complicated equipment and infrastructure more efficiently, accurately, and safely. Real-time defect detection and predictive maintenance are possible by integrating computer vision, advanced sensor technologies, and deep learning, and the proportion of operational downtime and overall safety can be increased (Santos et al., 2023; Merchá-Cruz et al., 2025). According to the studies, the AI-based systems, such as the smart helmet or robotic teleoperation station, not only enhance the occupational safety but also allow human-in-the-loop decision making, allowing critical insights to be successfully interpreted and acted on (Bęś et al., 2025; Yousefi et al., 2025; Khedr et al., 2025).

Moreover, the application of AI to the management of data, compliance with risks, and operational schemes based on knowledge contribute to enhanced reliability and regulatory compliance at dangerous workplaces (Komaragiri, 2024; Paleti, 2023; Martino et al., 2025). Use of AI-enhanced visual checks promotes the transition to the proactive maintenance approach and smart infrastructure surveillance, closing the divide between the potential and actual application of the technology (Haqu et al., 2025; Anthuvan et al., 2025).

Conclusively, the integration of AI and robotics with advanced sensing in the mining and heavy industry provides a paradigm shift in the practices of inspection: maximizing the operational efficiency, reducing the risk exposure, and ushering in new ideas of the industrial safety and equipment control (Santos et al., 2023; Merchán-Cruz et al., 2025).

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