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Deploying underground drones for real-time void detection, stope stability assessment, and predictive hazard analysis

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Abstract

Underground mining operations face persistent challenges associated with hidden voids, unstable stopes, and rapidly evolving geomechanically conditions that threaten both safety and productivity. Traditional monitoring methods such as manual inspections, static instrumentation, and periodic geotechnical surveys often lack the spatial reach, temporal frequency, and adaptive responsiveness required to detect early signs of instability. Recent advancements in autonomous drone technologies provide a transformative alternative, enabling real-time spatial intelligence in confined and GPS-denied environments. Equipped with LiDAR, multispectral imaging, thermal sensors, and visual–inertial navigation systems, underground drones can autonomously map complex subsurface geometries, identify hazardous anomalies, and acquire high-density data even in areas inaccessible to human workers. From a broad perspective, drone-enabled void detection enhances mine planning by revealing hidden cavities, unworked pockets, and irregular stopes that may compromise ground stability or disrupt production sequencing. Real-time stope stability assessment further strengthens operational safety by detecting stress-induced deformations, rock-mass deterioration, and early-warning indicators of potential collapses. These insights are critical for implementing timely remediation measures such as backfilling, reinforcement, or controlled re-entry protocols. The integration of drone-derived spatial data into predictive hazard-analysis frameworks represents a major leap toward proactive geotechnical risk management. Machine learning models and digital-twin simulations can now assimilate continuous drone observations to forecast instability progression, quantify risk zones, and support automated decision-making. This convergence of autonomous navigation, advanced sensing, and predictive analytics positions underground drones as essential components of next-generation mine safety systems. By delivering persistent situational awareness and high-resolution diagnostics, drone-based monitoring enables mining enterprises to transition from reactive hazard response to a fully predictive, data-driven operational paradigm.

Keywords: Underground Drones; Void Detection; Stope Stability; Predictive Hazard Analysis; Lidar Mapping; Autonomous Navigation

1. Introduction

1.1. Context of Underground Mine Safety Challenges

Underground mining environments present a combination of geological uncertainty, structural variability, and operational hazards that make real-time monitoring essential for sustaining safe production [1]. The presence of uncharted voids, irregular stopes, and rapidly evolving stress conditions creates pathways for rock falls, collapses, and air-quality disturbances that threaten worker safety and equipment integrity [2]. Many of these hazards develop without visible precursors, particularly in deep, high-stress mines where deformation accelerates unexpectedly.

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Complex spatial geometries, limited visibility, dust, and ventilation turbulence further hinder situational awareness and impede accurate mapping of changing rock-mass behavior [3]. As operations extend deeper to reach lower-grade ore bodies, the intensity of seismicity, stress redistribution, and unknown geological discontinuities increases significantly, raising the probability of undetected instability zones [4]. These evolving conditions demand monitoring systems capable of detecting minute structural and environmental changes before they escalate into large-scale failures. With production schedules becoming more compressed, mines require continuous hazard detection mechanisms that operate at high resolution and adapt to the pace of excavation. Without advanced sensing capabilities, critical changes in the underground environment may remain unnoticed, reinforcing the pressing need for innovative monitoring technologies [5].

1.2. Limitations of Traditional Subsurface Monitoring Methods

Conventional monitoring methods, although longstanding in mining practice, exhibit significant constraints when applied to modern high-risk underground operations. Manual inspections necessitate physical entry into unstable zones, exposing personnel to falls-of-ground, toxic gases, and equipment-related dangers [6]. Ground instruments such as extensometers, prisms, and stress meters capture localized deformation but cannot represent large-area conditions in real time, leaving gaps in spatial coverage [7]. Moreover, these systems provide intermittent rather than continuous measurements, limiting their ability to capture rapidly progressing hazards [8]. Borehole cameras and robotic crawlers offer partial improvement but struggle with navigation in irregular voids filled with debris or low-visibility conditions. Seismic and acoustic sensors deliver valuable early-warning indicators but require complex interpretation and cannot independently map the geometry of hazardous openings [9]. Together, these limitations restrict a mine's capacity for proactive hazard management and delay the identification of dangerous anomalies. As mining layouts grow more intricate, it becomes increasingly evident that traditional approaches alone cannot meet the demand for rapid, wide-area, and high-fidelity hazard detection [10].

1.3. Rise of Autonomous Drone Systems for Hazard Detection

Advances in autonomous drone technologies have introduced a paradigm shift in underground hazard detection by enabling high-precision, real-time assessment without placing personnel at risk [6]. Equipped with LiDAR, thermal imaging, multispectral sensors, and visual–inertial navigation systems, drones can autonomously navigate through narrow drifts, irregular stopes, and cluttered voids where traditional tools fail to operate reliably [1]. Their ability to generate dense three-dimensional point clouds and spectral maps allows rapid identification of hidden cavities, loose rock zones, and moisture-induced weakness areas that may precede structural failure [9]. Modern algorithms support collision-free navigation in GPS-denied environments, enabling continuous data collection even in poor visibility or dust-laden air. Drones also capture high-frequency updates, creating time-lapse models that reveal progressive deformation patterns critical for predicting hazardous conditions [3]. As autonomous flight control becomes more robust, drones are increasingly integrated into routine monitoring cycles, transforming underground hazard detection into a proactive, data-driven process supported by advanced sensing technologies [7].

2. Sensing And Navigation Foundations for Underground Drone Operations

2.1. Core Sensing Modalities in GPS-Denied Mining Environments

Underground mining conditions demand sensing technologies capable of producing reliable spatial, structural, and material information in environments where GPS is unavailable and visibility is frequently compromised. Modern drone-based sensing architectures combine LiDAR, multispectral imaging, thermal cameras, acoustic probing, and radar technologies to create an integrated situational awareness layer capable of detecting voids, mapping stope geometries, and identifying hazardous anomalies [7]. These modalities function by collecting physical and spectral signatures that reveal changes in rock mass behavior, moisture accumulation, or structural discontinuities that may precede instability events. The advantage of these sensors lies in their ability to operate amid dust, darkness, and geometrically constrained spaces that challenge traditional surveying methods [10].

LiDAR systems provide high-density point clouds that enable accurate reconstructions of underground cavities and stope walls, while multispectral and thermal sensors highlight mineralogical and thermal anomalies associated with water ingress or heat-generating stresses [12]. Acoustic and radar-based probing extend detection capability beyond visible surfaces, revealing hidden cavities, weak zones, or layered rock structures otherwise undetectable by optical methods [15]. Used together, these sensing tools form an adaptive detection framework capable of identifying both surface-level and deeply embedded hazards.

Integrated sensing also enhances temporal monitoring. By repeating drone flights at high frequency, operators can detect progressive deformation signatures, cavity expansion, and early formation of structural discontinuities long before major failures occur [9]. Sensor fusion algorithms combine point clouds, reflectance data, temperature gradients, and echo patterns into a unified digital environment, offering geotechnical teams a multidimensional representation of subsurface conditions. As underground mines grow deeper and more structurally complex, robust sensing modalities become indispensable for maintaining situational awareness, supporting predictive hazard assessment, and enabling safe autonomous drone navigation [14].

2.1.1. LiDAR for Structural Mapping and Void Profiling

LiDAR remains the cornerstone sensing modality for underground drone operations because of its ability to generate precise, high-resolution point clouds under challenging lighting and environmental conditions [11]. Its laser-based measurements are unaffected by darkness and maintain accuracy even when dust or suspended particulates attenuate optical imaging systems. By sweeping narrow beams across stope surfaces and void interiors, LiDAR constructs detailed three-dimensional models that reveal fractures, overbreak regions, discontinuities, and cavity geometries with centimeter-level fidelity [8]. These spatial reconstructions enable engineers to assess rock-mass behavior, detect hazardous overhangs, and identify previously unmapped cavities that may compromise ground stability. When integrated with SLAM frameworks, LiDAR also provides real-time localization support, allowing drones to navigate safely while simultaneously mapping void structures [16].

2.1.2. Multispectral and Thermal Imaging for Material and Moisture Anomalies

Multispectral and thermal imaging significantly extend the interpretive capabilities of underground drone systems by detecting material contrasts and temperature variations linked to geological or structural anomalies [7]. Multispectral sensors capture reflectance across various wavelength bands, enabling identification of moisture pockets, altered rock zones, oxidation surfaces, or clay-rich features associated with weakening rock masses [13]. Thermal imaging complements this by revealing heat signatures created by frictional stresses, warm ventilation flows, or water infiltration each of which may indicate evolving hazards. These imaging systems are particularly useful in areas where visual cues are minimal or obscured by dust, providing an additional diagnostic layer that enhances early hazard detection. Combined with LiDAR-based geometry, multispectral and thermal datasets strengthen decision-making for void detection and stope stability evaluation [12].

2.1.3. Acoustic and Radar-Based Probing for Hidden Cavities

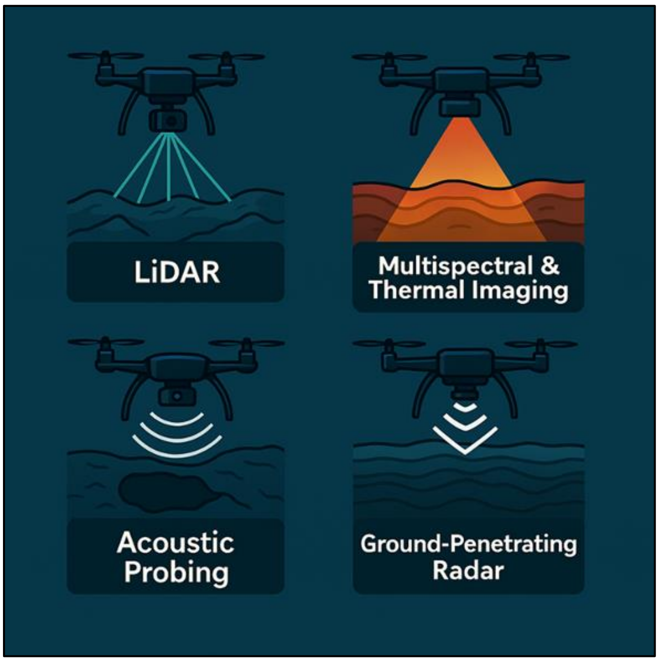

Figure 1 Overview of Key Sensor Modalities for Underground Drone Mapping

Acoustic and radar systems enable detection of subsurface voids that lack visible surface indicators. Acoustic probing interprets echo patterns and sound-wave attenuation to infer the presence of hollow regions behind stope walls or pillars [15]. Ground-penetrating radar provides higher-resolution subsurface imaging, revealing layered structures, weak zones, and discontinuities masked beneath rock surfaces [9]. These methods complement optical sensors by uncovering hazards not captured through line-of-sight imaging.

2.2. Navigation Algorithms for Confined, Dusty, and Geometrically Irregular Spaces

Navigation in underground mines requires advanced algorithms capable of maintaining stable localization within GPS-denied, dust-filled, and structurally complex environments. Visual–inertial navigation, LiDAR-SLAM, and probabilistic motion-estimation frameworks work together to correct drift, ensure obstacle awareness, and support real-time pathfinding [10]. These systems must withstand sudden airflow disturbances, low illumination, feature-poor surfaces, and narrow drifts that challenge both sensor reliability and flight control [14]. Continuous adaptation is essential: drones must navigate with minimal human intervention, avoid collisions, and maintain sufficient separation from walls, equipment, and irregular geological features. By merging sensor data and using redundancy across modalities, navigation algorithms enable safe flight in areas traditionally inaccessible to personnel [16].

2.2.1. Visual–Inertial Odometry (VIO) and SLAM Constraints

VIO and SLAM allow drones to estimate their position and orientation by fusing camera inputs with inertial measurements. In underground conditions, VIO compensates for rapid rotations, vibration, and transient loss of visual features [7]. SLAM provides simultaneous mapping and localization, enabling structured navigation through unknown cavities and stopes [11]. However, these algorithms face constraints when visibility is poor, when dust reduces feature detection, or when surface textures offer limited contrast. Integrating LiDAR improves robustness by providing geometric anchors that stabilize pose estimation [15].

2.2.2. Obstacle Avoidance and Adaptive Wall-Following

Obstacle-avoidance systems use real-time sensor scans to identify hazards such as protruding rock, narrow intersections, or machinery [9]. Adaptive wall-following algorithms maintain optimal distances from surfaces, enabling drones to navigate confined drifts while capturing high-quality data. These systems automatically adjust speed, heading, and elevation to compensate for bends, tight corners, and unpredictable ventilation flows [13]. By continuously updating hazard maps, obstacle-avoidance logic supports safe autonomous operation in the most geometrically irregular sections of the mine [14].

2.3. Environmental and Operational Constraints in Subsurface Flights

Underground flight performance is shaped by a combination of airflow instability, dust density, temperature fluctuations, and communication degradation. These conditions affect sensor reliability, power consumption, and drone maneuverability [8]. Understanding environmental constraints is therefore essential for maintaining data quality and flight stability throughout complex underground networks [12].

2.3.1. Dust, Darkness, Turbulence, and Communication Degradation

Dust clouds obscure visual sensors, reduce SLAM performance, and scatter LiDAR pulses, while darkness limits image-based navigation [16]. Turbulence from ventilation systems destabilizes flight paths, and irregular drift geometry creates signal dropouts that weaken communication links [10].

2.3.2. Battery, Heat, and Vibration Effects on Flight Performance

High temperatures accelerate battery depletion, while cold zones reduce power output. Mechanical vibration from rotor–wall interactions disrupt VIO and inertial readings [7]. Drones must therefore employ thermal management, vibration damping, and optimized power distribution to remain operational in confined my spaces [15].

3. Real-Time Void Detection and Spatial Intelligence

3.1. Principles of Void Geometry Extraction

Void geometry extraction forms the foundation of drone-based subsurface hazard detection, enabling engineers to identify spatial discontinuities, unmapped cavities, and hazardous openings that compromise underground stability. By deploying LiDAR, multispectral, thermal, and radar-assisted sensors, drones generate dense spatial datasets that accurately represent the internal structure of stopes, drifts, and fractured rock zones [15]. These datasets must be processed through sophisticated reconstruction algorithms to distinguish natural geological voids from operational cavities created during excavation.

The fundamental principle involves characterizing the three-dimensional shape, continuity, and spatial distribution of void networks. High-density point clouds reveal stope boundaries, the geometry of overbreak and underbreak zones, and the extent of cavity propagation along weakened rock-mass planes [19]. These spatial datasets are especially important in areas where geological structures intersect mine workings, increasing the risk of undetected chambers or unstable hanging walls.

Spectral, density, and reflectance variations extracted from multispectral and thermal sensors complement geometric data by highlighting regions where moisture ingress, oxidation, or altered mineral composition may indicate void formation behind the visible rock face [17]. When integrated with acoustic or radar-based probing, drone systems are capable of identifying air-filled or partially collapsed cavities located behind walls or pillars. Through continuous monitoring across multiple flight missions, progressive deformation or cavity expansion can be tracked with high temporal fidelity, strengthening predictive hazard modelling and risk quantification [22]. These principles ensure that void geometry extraction becomes a systematic, data-rich workflow capable of supporting real-time decision-making in underground operations [24].

3.1.1. Point Cloud Processing and Surface Reconstruction

Point cloud processing begins with the alignment and filtering of LiDAR returns, allowing drones to reconstruct accurate surface models even in dust-laden or geometrically complex voids [18]. Algorithms identify noise, outliers, and incomplete returns to ensure reliable mesh generation. Once cleaned, the point cloud is converted into polygonal surfaces that represent stope walls, void contours, and fracture propagation pathways with high fidelity. This enables engineers to identify irregular or hazardous geometries, including overhanging slabs, narrow roof cavities, or sharp discontinuities indicative of stress redistribution [14]. Advanced reconstruction techniques also quantify void volume, surface roughness, and wall divergence angles, supporting detailed geotechnical analysis and predictive modelling [21].

3.1.2. Reflectance, Density, and Spectral Anomalies for Hidden Cavities

Reflectance and density anomalies serve as key diagnostic indicators for identifying concealed cavities behind visible rock surfaces. Multispectral sensors capture variations in wavelength absorption stemming from moisture, mineral alteration, or oxidation—all of which may signal weakening rock mass or air-filled zones [16]. Thermal imaging identifies irregular heat dissipation patterns caused by voids, ventilation leakage, or localized water pockets. These thermal gradients often correspond to structural separations that are not evident through geometry alone [20]. Density-based anomalies detected through radar or acoustic probing further strengthen interpretation by revealing hollow or partially collapsed regions hidden within the rock mass [23]. Combined, these anomalies guide targeted intervention and advanced hazard modelling.

Table 1 Comparison of Void Detection Techniques and Their Spatial Resolution Limits

Void Detection Technique	Primary Sensing Principle	Detectable Void Types	Spatial Resolution Limits	Strengths	Limitations
LiDAR-Based Mapping	Laser time-of-flight measurement producing dense point clouds	Open cavities, stope walls, overbreak/underbreak regions	High resolution (1–5 cm) depending on sensor class and dust conditions	Accurate geometry capture; unaffected by low lighting; excellent for cavity profiling	Performance reduced by dense dust clouds; cannot detect voids behind intact rock surfaces
Multispectral Imaging	Reflectance variation across multiple wavelength bands	Moisture-related void precursors, altered or weakened zones	Medium resolution (10–20 cm) depending on illumination and spectral bandwidth	Identifies material anomalies linked to hidden cavities; sensitive to moisture and mineral alteration	Limited penetration depth; requires stable illumination; sensitive to dust

Thermal Imaging	Surface temperature gradient analysis	Water-filled cavities, ventilation-connected voids, heat-related failure zones	Medium resolution (5–15 cm) depending on thermal contrast	Reveals hidden voids via heat anomalies; effective for moisture tracking and ventilation leakage	Cannot resolve cavity geometry directly; influenced by ventilation and ambient heat
Acoustic Probing	Sound-wave reflection and attenuation through rock mass	Air-filled voids, partially collapsed or hidden cavities behind walls	Variable resolution (approx. 20–50 cm) depending on rock density and noise	Detects voids behind rock faces; useful in acoustically favorable environments	Susceptible to machinery noise; reduced accuracy in highly fractured rock
Ground-Penetrating Radar (GPR)	Electromagnetic wave propagation and subsurface reflection	Subsurface voids, weak zones, delamination's	Moderate to high resolution (5–30 cm) depending on antenna frequency	Penetrates beyond visible surfaces; effective for layered structures	Limited by rock conductivity; penetration depth reduced in wet or mineralized rock
Integrated Sensor Fusion	Combination of LiDAR, radar, thermal, and spectral signatures	Complex void systems, evolving cavities, multi-factor instability zones	Very high effective resolution (1–10 cm) through combined datasets	Most reliable for early detection; captures multi-dimensional hazard indicators; reduces false negatives	Higher computational demand; requires advanced SLAM and fusion algorithms

3.2. Automated Void Classification and Hazard Prioritization

Automated void classification transforms raw geometric and spectral datasets into actionable hazard categories, enabling real-time risk assessment in complex underground environments [24]. Machine learning and deep neural networks analyze thousands of geometric descriptors such as curvature, depth, surface roughness, and volumetric expansion to differentiate between natural geological cavities, operational stopes, overstressed voids, and hazardous overbreak's [15]. These algorithms continuously improve as more data is collected, allowing classification accuracy to increase over time.

Hazard prioritization frameworks integrate geometric complexity, deformation signatures, moisture anomalies, and historical failure patterns to automatically rank voids based on their destabilization potential. This tiered ranking system supports rapid decision-making and ensures that geotechnical teams direct resources toward the most urgent hazards.

Specialized algorithms generate color-graded heat maps that visually encode risk levels across stope walls, pillars, and drift intersections [19]. High-risk areas such as expanding cavities, voids near fault zones, or regions with elevated moisture content are highlighted for immediate inspection or reinforcement [17]. These heat maps are dynamically updated as drones conduct sequential flights, allowing operators to track risk evolution over time.

When integrated with real-time alerting systems, automated classification enables early detection of dangerous voids long before they progress toward collapse, enhancing operational resilience and improving worker safety in high-stress mining environments [22].

3.2.1. Machine Learning Models for Void Type Identification

Machine learning models classify voids by analyzing spatial, spectral, and thermal signatures extracted from drone datasets. Convolutional neural networks interpret geometric patterns, while decision-tree and ensemble models identify relationships between reflectance anomalies, fracture orientations, and cavity depth [20]. These models provide robust classification even in noisy or partially occluded environments, outperforming manual interpretation in speed and consistency [14]. Through continual retraining on historical and new datasets, classification accuracy improves significantly over time.

3.2.2. Heat-Map Generation and Risk Ranking Algorithms

Risk-ranking algorithms assign priority to detected voids by evaluating structural conditions such as cavity expansion rate, proximity to stressed pillars, and associated moisture signatures [23]. The system generates heat maps that highlight hazard zones using graded coloration, enabling geotechnical teams to visualize risk quickly [18]. These maps are dynamically updated during repeated drone surveys, making them effective for monitoring progressive instability. Automated ranking ensures that high-risk anomalies are flagged immediately for engineering intervention [16].

3.3. Integration of Void Maps into Operational Mine Planning

Void maps play a critical role in enhancing mine planning by providing spatially explicit insights into hazardous openings and areas requiring reinforcement. These maps help engineers optimize excavation sequencing, ventilation routing, and ground-support installations based on accurate void geometry and hazard classification data [21]. They also strengthen long-term planning by highlighting zones unsuitable for infrastructure placement or stope expansion.

3.3.1. Updating Drift, Stope, and Pillar Development Plans

Integrating void maps into planning workflows ensures that drift development avoids hazardous cavities and that stope designs incorporate realistic ground-support requirements [24]. Pillar dimensions and reinforcement density can be adjusted in real time based on cavity proximity and extent [19].

3.3.2. Alerts for Unexpected or Illegal Workings

Void detection systems also flag anomalous cavities inconsistent with planned excavation layouts. These may indicate illegal workings, unauthorized tunneling, or unknown historical voids that pose severe structural risks [15]. Automated alerts guide rapid investigation and safety intervention [17].

4. Drone-Assisted Stope Stability Assessment

4.1. High-Fidelity Geometry Capture for Structural Interpretation

High-fidelity geometric data is essential for understanding the structural integrity of stopes and excavated voids, particularly in deep underground mines where stress redistribution and geological variability increase the likelihood of instability. Drone-mounted LiDAR, visual–inertial odometry (VIO), and high-resolution imaging systems generate dense spatial datasets that reveal subtle surface variations, discontinuities, and deformation signatures that may precede rock-mass failure [22]. These datasets offer far greater precision and coverage than manual inspections, enabling continuous interpretation of wall geometry even in areas inaccessible to personnel.

Through repeated drone flights, sequential point clouds can be compared to quantify changes in cavity dimensions, wall roughness, and geometric divergence along bedding planes or joints. Such temporal analysis is critical for detecting early indicators of overbreak propagation or localized bending of stope walls under elevated stress [24]. High-density geometry capture also supports numerical modelling, allowing geotechnical engineers to calibrate boundary conditions, simulate stress-flow pathways, and validate rock-mass behavior against observed deformation [27].

By integrating geometric fidelity with spectral and thermal indicators, drones provide a multi-layered structural analysis framework that improves safety and operational decision-making. This synergy enables earlier identification of emerging instabilities and strengthens predictive hazard assessments across the stope lifecycle [29].

4.1.1. Overbreak/Underbreak Detection

Overbreak and underbreak conditions significantly influence ground-support design, excavation efficiency, and long-term structural stability. Drone-based LiDAR provides detailed surface meshes that delineate deviations from planned excavation profiles, highlighting zones where excessive breakage or insufficient extraction has occurred [23]. Overbreak regions often reflect weakened rock or excessive explosive energy release, while underbreak areas indicate unfragmented blocks that may detach unpredictably under stress.

Temporal mapping enhances detection accuracy by revealing progressive deformation or cavity expansion not visible from a single survey [25]. Autonomous drones enable precise comparisons between planned and actual geometries, reducing reliance on manual measurements that are limited in coverage and exposed to safety risks [28]. Identifying these deviations early allows engineers to reinforce vulnerable areas or adjust future blasting patterns.

4.1.2. Joint, Fracture, and Bedding Plane Characterization

Accurate characterization of structural discontinuities is a critical component of stope stability assessment. Drone-captured point clouds reveal joint spacing, orientation, persistence, and aperture variations with exceptional resolution [26]. These attributes influence block size distribution, failure modes, and the likelihood of wedge or planar failures. Thermal and multispectral data further refine interpretation by highlighting moisture infiltration or altered mineralogical zones associated with fracture propagation [30].

Automated feature-extraction algorithms classify discontinuity sets and quantify their geometric relationships, enabling robust geomechanically modelling. Such analysis improves predictions of rock-mass behavior under changing stress conditions and enhances the reliability of stope-support design [22].

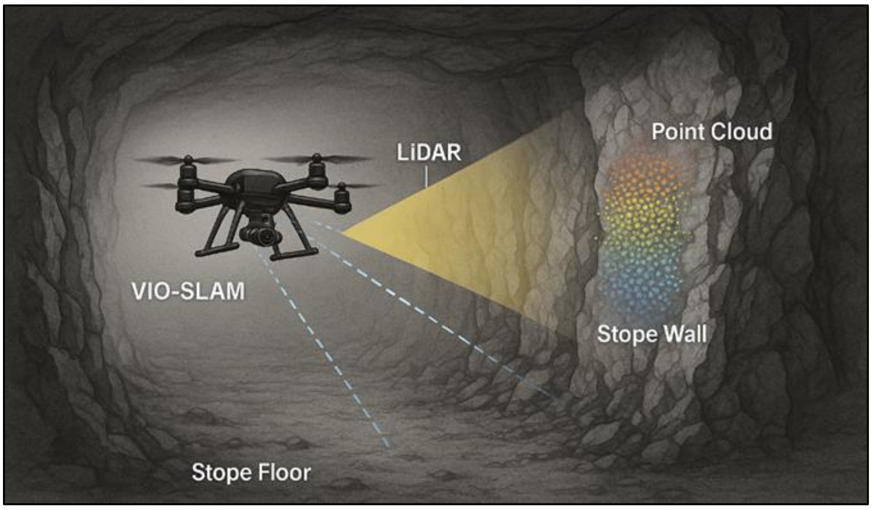

Figure 2 Drone-Based Structural Mapping of Stope Surfaces Using LiDAR and VIO-SLAM

4.2. Real-Time Geomechanically Indicators and Rock-Mass Behavior

Real-time geomechanically indicators detected through drone-based sensing significantly enhance situational awareness during active mining operations. High-frequency LiDAR, thermal imaging, and spectral reflectance measurements capture early warning signs of deformation, excessive stress accumulation, and weakening rock-mass conditions that precede hazardous failures [27]. These indicators allow engineers to anticipate instability rather than respond reactively, strengthening overall ground-control strategies.

Drone systems detect subtle changes in stope-wall geometry by comparing sequential point clouds. Minor wall bulging, cavity expansion, or micro-fracture formation can signify elevated tensile stress or rock-mass deterioration [23]. Thermal anomalies can indicate frictional heating linked to material displacement or localized ventilation disruptions, while spectral variations reveal moisture pathways that weaken cohesion or increase pore pressure [29].

When combined, these geomechanically signals provide a comprehensive understanding of rock-mass behavior under variable loading conditions. Drones collect these indicators without exposing personnel to risky environments, enabling continuous monitoring in deep or inaccessible stopes [24].

4.2.1. Deformation Tracking and Progressive Damage Signals

Progressive deformation often precedes large-scale rock-mass failures, making real-time deformation tracking essential for safe operations. Drones capture minute geometric changes by comparing multi-temporal point clouds, identifying wall displacement, cavity growth, or rock-block rotation with high accuracy [30].

Machine learning algorithms trained on deformation patterns detect abnormal trends that may correspond to stress-induced cracking or progressive slabbing [25]. These insights allow engineers to take early action before conditions evolve into falls of ground or catastrophic collapses. Remote tracking reduces reliance on manual inspections and provides a consistent, high-resolution understanding of structural changes [22].

4.2.2. Moisture, Temperature, and Ventilation Effects on Stability

Moisture and temperature variations directly influence rock-mass strength, while ventilation patterns affect both structural behavior and sensor performance. Thermal imaging reveals heat gradients associated with stress movement, ventilation leakage, or water ingress behind stope walls [28]. Multispectral reflectance highlights moisture-rich zones where weak clay minerals or altered rock may accelerate failure progression [29].

Drone-based environmental monitoring also identifies ventilation-induced turbulence, which may destabilize loose materials along fractured surfaces [24]. Integrating these environmental indicators improves predictive assessments of stope stability under dynamically changing underground conditions [26].

4.3. Autonomous Stope Hazard Flagging

Autonomous hazard flagging enables drones to detect, classify, and prioritize potential failure zones in real time. Using advanced algorithms, drones analyze geometric, thermal, and spectral signatures to identify hazardous patterns associated with rock falls, cavity expansion, or structural instability [27].

These systems assign risk scores to detected features using multi-criteria decision frameworks, integrating deformation rates, discontinuity geometry, stress concentration indicators, and environmental anomalies [22]. The automated nature of hazard flagging reduces human interpretation bias and accelerates response times in high-risk areas.

4.3.1. Machine-Learned Instability Patterns

Machine-learning models trained on historical failure cases identify instability signatures such as wedge formation, spalling patterns, or increasing void divergence [30]. These models use geometric descriptors, heat distribution patterns, and reflectance anomalies to detect unseen hazards that traditional inspection methods may overlook [23]. Continuous training enhances classification accuracy over time, allowing the system to adapt to new geological settings [28].

4.3.2. Trigger Signatures for Falls-of-Ground Early Warning

Falls of ground often exhibit precursor signals, including micro-deformation, thermal irregularities, and moisture concentration shifts. Drones detect these signatures and generate early-warning alerts using predefined thresholds and anomaly-detection algorithms [26]. The ability to rapidly flag impending instability gives operators valuable time to implement reinforcement measures, restrict access, and adjust production schedules [22]. These early warnings form the basis of proactive ground-control strategies that strengthen operational resilience.

5. Predictive Hazard Analysis and Digital-Twin Integration

5.1. Data Fusion and Real-Time Hazard Modeling Architectures

Modern underground drone systems generate diverse datasets spanning geometric, thermal, spectral, inertial, and radar-derived domains, making data fusion central to real-time hazard modeling. When combined effectively, these heterogeneous data streams create a unified situational-awareness environment that captures subtle precursors of instability across stopes, pillars, and drifts [28]. The core challenge lies in synchronizing inputs acquired under fluctuating lighting, dust interference, and turbulent airflow, conditions that can degrade sensor precision. Fusion architectures mitigate such limitations by integrating redundant measurements, correcting for sensor biases, and harmonizing spatial references.

By merging high-density point clouds with thermal gradients, reflectance anomalies, and acoustic echoes, fused models provide a multifaceted view of rock-mass behavior. These models can detect overlapping hazard indicators such as cavity growth accompanied by heat anomalies or moisture accumulation which single-sensor systems might overlook [32]. Real-time fusion pipelines also support dynamic updates, enabling drones to revise hazard assessments during flight missions. Algorithms quantify uncertainty across data layers, ensuring decisions rely on robust correlations rather than isolated anomalies.

Sensor fusion extends beyond structural assessment. Environmental variables such as ventilation flow, temperature oscillations, and gas pathways are incorporated to refine predictions of deformation or fracture propagation under varying stress conditions [30]. These fused datasets populate hazard-modeling engines that classify risk levels, generate early-warning signals, and support automated intervention through mine-control systems. As drone fleets expand, multi-platform fusion integrating data from multiple simultaneous flights creates mine-wide risk snapshots with unprecedented resolution [34].

Ultimately, real-time fusion architectures transform drone observations into predictive intelligence, enabling a shift from episodic monitoring to continuous, data-driven hazard assessment.

5.1.1. Combining LiDAR, Thermal, VIO, and Radar Inputs

LiDAR supplies geometric accuracy, capturing cavity shapes, wall deformation, and discontinuity evolution. Thermal sensors highlight friction zones, ventilation leakage, or water seepage that affect stability [29]. Visual–inertial odometry (VIO) enhances localization and detects motion anomalies along rock surfaces, while radar contributes subsurface insights where cavities or weak zones exist behind stope walls [31].

Fusion of these inputs creates a composite hazard map where geometry, temperature, reflectance, and subsurface density variations are layered into a single interpretation model. Cross-referencing LiDAR-derived bulging zones with thermal and radar anomalies improves the accuracy of identifying progressive failures. Each modality supports the limitations of another: thermal and radar compensate for LiDAR reductions in dust, while geometric anchors stabilize VIO-based navigation in feature-poor zones [35]. This synergy strengthens early-warning capability and provides high confidence in hazard classification.

5.1.2. Role of Onboard and Edge Computing

Onboard computing enables drones to process raw sensor data immediately, reducing latency and ensuring that hazard indicators are detected in real time. Localized processing is vital for underground environments where communication links degrade, preventing seamless cloud-based analysis [28]. Onboard systems perform feature extraction, thermal segmentation, deformation tracking, and anomaly identification while the drone is still in flight.

Edge-computing nodes installed in the mine such as underground servers or ruggedized processing hubs aggregate data from multiple drones, enabling advanced modeling and multi-sensor fusion beyond what onboard processors can handle [33]. These nodes run machine-learning models, perform risk scoring, and synchronize outputs with mine-control systems despite intermittent network conditions. Edge computing ensures continuity, allowing hazard models to update automatically even when the drone fleet operates deep underground [30]. Together, onboard and edge architectures form a resilient computing ecosystem that supports predictive hazard analysis at operational speed.

Table 2 Predictive Hazard Indicators and Their Associated Drone-Derived Data Inputs

Predictive Hazard Indicator	**Associated Drone-Derived Data Inputs**	**Primary Detection Modalities**	**Predictive Value / Use Case**
Progressive Wall Deformation	Multi-temporal LiDAR point clouds; VIO pose changes; surface divergence metrics	LiDAR, VIO-SLAM	Early detection of bulging, slabbing, and structural drift indicating potential stope failure.
Cavity Expansion Rate	Sequential void geometry models; volumetric change analysis; deformation vectors	LiDAR, Radar	Identifies growing voids or hidden cavity propagation behind rock faces.
Thermal Instability Patterns	Heat gradients; localized temperature anomalies; ventilation-driven thermal displacement	Thermal Imaging, Environmental Sensors	Detects frictional heating, ventilation leakage, or heat accumulation linked to rock movement.
Moisture Accumulation and Water Pathways	Spectral moisture signatures; thermal cooling zones; reflectance anomalies	Multispectral, Thermal	Predicts weakened cohesion in clay-rich or fractured zones; indicator of potential collapses or seepage.

Rock-Mass Weakening via Spectral Alteration	Wavelength absorption trends; oxidation indicators; altered mineral composition	Multispectral Imaging	Identifies altered or decayed rock zones susceptible to spalling or structural degradation.
Ventilation and Airflow Disruptions	Airflow turbulence metrics; thermal drift patterns; particulate movement	Thermal, VIO, Environmental Sensors	Highlights ventilation blockages that may shift stress distributions or accelerate cavity deterioration.
Subsurface Hollow or Weak Zones	Radar reflectance attenuation; acoustic echoes; density contrast signatures	Ground-Penetrating Radar, Acoustic Probing	Reveals voids, delamination, or layered weaknesses beyond visible surfaces.
Micro-Failure Precursors	High-frequency vibration signatures; small-scale geometric noise patterns; surface texture change	VIO, LiDAR Micro-Deformation	Predicts early micro-cracking and brittle deformation before large-scale failure.
Stress Redistribution Hotspots	Combined thermal, deformation, and spectral gradients; multi-layer anomaly convergence	LiDAR + Thermal + Spectral Fusion	Flags areas of concentrated geotechnical stress requiring reinforcement or restricted access.
Unstable Pillar or Back Conditions	Pillar geometry changes; moisture hotspots; cavity development; thermal contrasts	LiDAR, Multispectral, Radar	Supports early-warning systems for pillar overstressing or impending back (roof) collapse.

5.2. Digital Twin Systems for Dynamic Risk Forecasting

Digital twin systems represent the next evolution in geotechnical hazard management, creating continuously updated virtual replicas of underground my environments. By integrating drone-derived geometry, thermal profiles, spectral signatures, and deformation metrics, digital twins provide a high-fidelity depiction of stope evolution under changing stress conditions [31]. These systems run predictive algorithms that simulate future rock-mass behavior, enabling engineers to anticipate failure mechanisms before they manifest physically.

Digital twins operate as living models. Each drone flight uploads new geometric and environmental information, recalibrating stress distribution maps, boundary conditions, and hazard indices. This dynamic recalibration is essential in deep mines where extraction sequences induce rapid stress redistribution [28]. Real-time forecasting allows geotechnical teams to evaluate the likelihood of collapses, pillar overstressing, or cavity expansion across multiple time horizons.

Beyond prediction, digital twins enhance scenario planning. Engineers can simulate interventions such as reinforcement installation, stope redesign, or altered ventilation and visualize structural responses before implementing changes operationally [34]. Drone-fed twins thus serve as both diagnostic and prescriptive systems.

5.2.1. Continuous Updating of Geomechanically Models

Geomechanically models depend on accurate geometry and stress-field inputs. Drones supply high-density updates to cavity dimensions, joint configurations, and wall deflections that directly influence stability calculations [29]. Each update improves model accuracy and reduces prediction uncertainty. Machine learning algorithms refine constitutive parameters by correlating observed deformation patterns with predicted outcomes, creating adaptive models that evolve with the mine environment [32].

5.2.2. Scenario Simulation and Real-Time Risk Visualization

Digital twins simulate thousands of structural scenarios, quantifying the probability of failure under varying load conditions, geological settings, or operational decisions [28]. Visual dashboards translate these simulations into spatial heat maps that highlight at-risk regions such as overstressed pillars or expanding voids [35]. Real-time visualization allows supervisors to monitor hazard evolution as drone data streams into the twin. Combined with near-real-time deformation tracking and environmental sensing, these simulations form the basis of predictive geotechnical intelligence and early-warning systems.

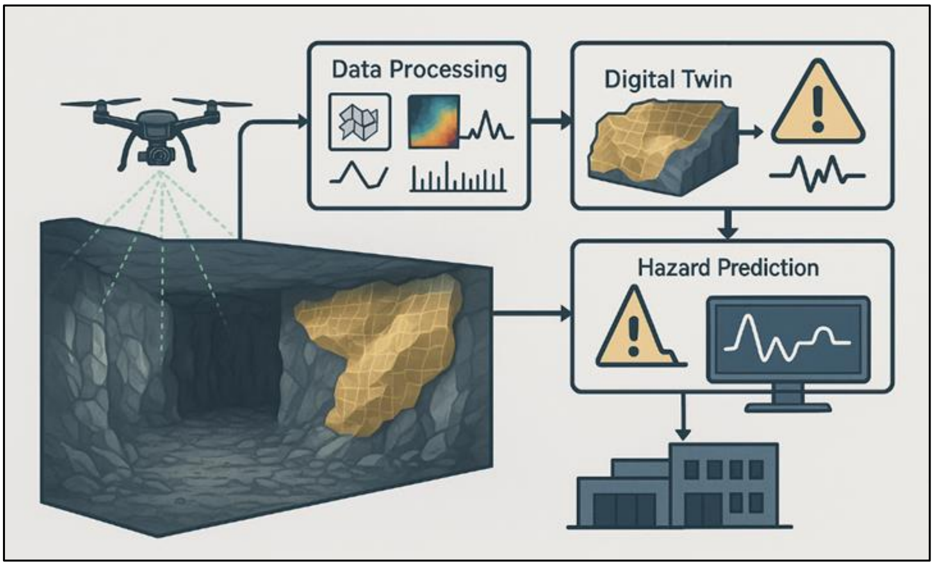

Figure 3 Digital-Twin Workflow Integrating Drone Data for Hazard Prediction

5.3. Integration with Mine Control Rooms and Decision Support Systems

Integrating drone-derived hazard intelligence into centralized mine-control rooms streamlines operational decision-making. Data fusion outputs, predictive risk scores, and deformation alerts feed directly into control-center dashboards, ensuring that supervisors maintain situational awareness even under rapidly evolving conditions [33]. Automated decision-support algorithms interpret these insights and recommend targeted interventions—such as restricting access, modifying blasting schedules, or reinforcing high-risk areas [30]. Integration ensures that drone data does not remain siloed but feeds into mine-wide risk management frameworks.

5.3.1. Automated Alerts and Remote Intervention

Automated alerts notify operators when hazard indicators exceed predefined thresholds, triggering immediate review or intervention. Alerts may concern sudden cavity expansion, spectral moisture spikes, unusual thermal gradients, or abrupt deformation patterns [34]. Remote-intervention systems can halt equipment, restrict worker entry, or adjust ventilation settings automatically, enhancing safety layers across critical zones [29].

5.3.2. Updating Mine-Wide Safety Dashboards and Workflows

Drone-derived risk layers update safety dashboards with real-time structural, environmental, and geomechanically indicators [28]. These updates help refine shift planning, ground-support deployment, and inspection schedules. By embedding continuous drone intelligence into daily workflows, mines transition toward proactive, predictive hazard management [35].

6. Deployment, Operationalization, And Regulatory Considerations

6.1. Practical Deployment Frameworks and Mission Planning

Deploying underground drones at scale requires a structured operational framework that coordinates mission planning, risk management, hardware readiness, and integration with existing my workflows. Unlike surface environments, underground spaces present confined geometries, unpredictable airflow, variable lighting, and complex communication pathways, all of which influence the preparation and execution of drone flights [34]. Mission planning therefore begins with detailed mapping of drifts, stopes, and ventilation infrastructure, allowing operators to predefine flight corridors that reduce collision risk and maximize sensor coverage.

Drone platforms must undergo pre-flight checks, including calibration of LiDAR, thermal, and inertial sensors to ensure reliability in dust-laden or vibration-prone areas [36]. Environmental forecasts such as expected blasting cycles or ventilation shifts must also be factored into scheduling to minimize disturbances during missions. Effective deployment frameworks incorporate real-time monitoring tools that allow control-room operators to track drone trajectories, battery levels, and navigation status as the mission progresses [35].

Deployment planning extends beyond individual flights; mines increasingly adopt routine drone schedules, integrating data updates into daily or weekly ground-control assessments. This systematic approach ensures consistent detection of voids, deformation patterns, and environmental anomalies. As autonomy improves, mission planning will rely more on automated route generation and self-optimizing flight sequences that adjust to dynamic underground conditions [37].

6.1.1. Safety Protocols for Autonomous Underground Flights

Safety protocols form the backbone of drone deployment, particularly in GPS-denied, confined mining environments. Before each mission, risk assessments identify zones with unstable ground, hazardous gases, or restricted clearances that require controlled navigation profiles [33]. Collision-avoidance logic, wall-following constraints, and emergency-return functions must be validated to ensure the drone can respond safely to unexpected obstacles or sensor degradation.

Redundant communication strategies such as multi-band radio links or autonomous fallback behaviors are essential when signal interruptions occur. Safety procedures also mandate no-entry zones for personnel during flights to prevent interference and reduce exposure to potentially unstable areas [38]. Together, these protocols ensure that autonomous operations maintain high reliability and minimize operational hazards.

6.1.2. Multi-drone Coordination and Coverage Optimization

Coordinating multiple drones enhances coverage and reduces inspection time across large stope networks. Multi-agent algorithms synchronize flight paths to prevent collisions and optimize data overlap for fusion processing [39]. Staggered launch windows and shared hazard maps allow drones to operate cooperatively even in complex, irregular void geometries. This coordination significantly increases the efficiency of structural and geotechnical data collection.

6.2. Regulatory, Ethical, and Workforce-Training Dimensions

As drone systems become integral to underground hazard detection, regulatory and ethical considerations grow in importance. Mines must comply with operational standards governing autonomous equipment, data security, and environmental safety. Regulations may require documentation of drone capabilities, operator training certifications, and emergency procedures to ensure accountability and minimize legal exposure [34]. Ethical considerations arise when drone data includes imagery of personnel or production-sensitive areas, making strict data-governance frameworks essential for privacy preservation and permissible usage [40].

A successful adoption strategy also requires specialized workforce training. Technicians must understand drone maintenance, calibration, fail-safe operation, and real-time data interpretation. Integrating drone teams into existing engineering and ground-control groups ensures cohesive hazard management. Training programs should develop competency in autonomy supervision, mission planning, and sensor diagnostics, enabling staff to effectively manage increasingly automated systems [37].

6.2.1. Data Privacy, Liability, and Operational Permissions

Drone-collected data may capture sensitive operational layouts, equipment states, or worker positions. Mines must implement access controls, encryption, and retention policies to ensure compliance with data-privacy regulations [33]. Liability frameworks determine responsibility in cases of drone malfunction or incorrect hazard interpretation, while operational permissions define who is authorized to deploy and review drone-based monitoring outputs [40].

6.2.2. Up-skilling Technicians and Integrating Drone Teams

As drone operations expand, technicians must be trained in sensor management, autonomy supervision, and data analytics. Competence in interpreting LiDAR, thermal, and radar signatures ensures that collected data informs geotechnical decisions accurately [39]. Integrating drone operators into ground-control teams strengthens collaboration and enhances the speed of hazard-response workflows [36].

6.3. Cost-Benefit Analysis and Return on Investment

Drone deployment offers significant financial and safety advantages by reducing manual inspection burdens, improving hazard forecasting accuracy, and decreasing downtime linked to unexpected collapses or operational disruptions [35]. Cost-benefit assessments evaluate reductions in survey time, improvements in equipment lifespan, and efficiency gains in both production and ground-control planning [38].

6.3.1. Reduction in Survey Time and Hazard Exposure

Automated drone flights complete structural surveys in minutes rather than hours, significantly reducing labor time and preventing worker exposure to unstable voids or high-risk stopes [33]. These efficiency gains produce measurable savings in operational scheduling and personnel allocation.

6.3.2. Equipment Lifespan Extension and Downtime Reduction

By detecting voids, deformation, and environmental anomalies before they escalate, drones contribute to better maintenance planning and reduced stress on infrastructure [34]. Early detection prevents equipment damage and minimizes downtime, enhancing overall return on investment [37].

7. Conclusions And Future Directions

7.1. Summary of Technological Contributions

The integration of underground drones into modern mining operations has fundamentally transformed subsurface hazard detection, structural assessment, and geotechnical decision-making. Through advancements in LiDAR mapping, multispectral imaging, thermal diagnostics, radar probing, and visual–inertial navigation, drones now deliver high-fidelity spatial and environmental data from areas previously inaccessible or too dangerous for personnel. These sensing capabilities, combined with autonomous navigation and real-time data fusion, enable continuous detection of voids, tracking of structural deformation, and identification of early-stage instability patterns. Machine-learning classification models elevate these insights by automating void categorization, risk scoring, and detection of precursor failure signatures. When integrated into digital-twin systems and mine-control platforms, drone-derived intelligence enhances predictive hazard modeling, supports proactive ground control, and streamlines operational decision workflows. Collectively, these technological contributions mark a decisive shift from reactive, labor-intensive monitoring practices to a predictive, data-driven framework for underground safety management.

7.2. Long-Term Vision for Fully Autonomous Underground Hazard Management

Looking forward, fully autonomous underground hazard management aims to establish a self-sustaining ecosystem where drones, sensors, and digital-twin platforms operate collaboratively with minimal human oversight. Future drone fleets will autonomously schedule missions, self-optimize flight paths based on changing geotechnical conditions, and continuously update mine-wide risk models. Expanded sensor integration such as hyperspectral imaging, microseismic coupling, and advanced radar tomography will further enhance subsurface visibility and predictive accuracy. Artificial-intelligence systems will evolve into autonomous geotechnical advisors capable of forecasting failures, recommending reinforcement strategies, and orchestrating automated interventions through mine-control systems. Multi-drone cooperation will become standard, enabling synchronized cavity inspection, stope stability mapping, and environmental monitoring on a mine-wide scale. Ultimately, the long-term vision centers on a fully interconnected subterranean monitoring network where continuous drone intelligence forms the backbone of safer, more efficient, and highly automated mining environments.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclsoed.

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