

Semantic-Aware Privacy-Preserving Mobile Lithology Intelligence: A Deep Learning Framework for Rock Image Recognition, Geological Interpretation, and Secure Field Trajectory Analytics

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KEYWORDS

lithology recognition, deep learning, mobile geology, semantic trajectory privacy, rock image classification, transfer learning, location privacy.

ABSTRACT

Background: Contemporary geological intelligence is increasingly shaped by two technological trajectories that are usually discussed separately: deep learning-driven lithology recognition from rock images and privacy-preserving analytics for mobile location and trajectory data. The first trajectory has rapidly advanced through convolutional neural networks, transfer learning, lightweight mobile models, and image-based mineral recognition, enabling increasingly accurate identification of lithology from drill cores, thin sections, fresh rock surfaces, borehole images, and field photographs (Marmo et al., 2005; Chatterjee, 2013; Izadi et al., 2017; Liu et al., 2020; Alzubaidi et al., 2021; Zhang et al., 2024). The second trajectory has evolved through semantic trajectory mining, geo-indistinguishability, differential privacy, semantic-aware privacy preservation, and location privacy surveys, highlighting the vulnerability of mobile users to inference attacks when movement data reveal behavioral and spatial patterns (Andrés et al., 2013; Zheng, 2015; Primault et al., 2019; Jiang et al., 2021; Qiu et al., 2023). Yet the field deployment of mobile lithology systems inherently joins these domains, because rock image acquisition, drill-site inspection, field traverses, and smartphone-assisted recognition generate sensitive trajectory traces.

Objective: This article develops a unified research framework for privacy-preserving mobile lithology intelligence by integrating advances in geological image recognition and semantic trajectory privacy.

Methods: Through a structured synthesis of the provided references, the study constructs a multilayer conceptual architecture linking rock image acquisition, deep feature extraction, transfer learning, lightweight inference, semantic context modeling, and privacy-preserving trajectory management. The article analyzes the theoretical compatibility of convolutional image intelligence and location privacy mechanisms under field geology conditions.

Results: The analysis indicates that geological image recognition systems become operationally stronger when visual inference is combined with semantic context, but they also become privacy-riskier because contextualized field trajectories increase re-identification potential. A robust mobile lithology platform therefore requires joint optimization of classification accuracy, geological interpretability, computational portability, and behavioral-semantic privacy preservation. The proposed framework demonstrates how deep visual models, semantic fusion, and trajectory protection mechanisms can coexist without reducing geological usability to purely anonymous yet contextless data.

Conclusion: A next-generation geological field intelligence system should not treat lithology recognition and location privacy as separate engineering problems. It should instead operate as a secure semantic pipeline in which mobile rock recognition benefits from trajectory-aware context while trajectory exposure is limited through differentiated privacy controls. This integrated perspective provides a new direction for trustworthy

INTRODUCTION

The digital transformation of geological investigation has moved far beyond the traditional boundaries of manual field notes, hand-lens inspection, and purely descriptive petrography. In recent decades, the geosciences have increasingly incorporated computational vision, machine learning, geochemical interpretation, image-based mineral discrimination, and intelligent mobile systems into core investigative workflows. What once depended exclusively on human visual expertise is now being reformulated through automated pattern recognition, feature learning, and real-time inferential support. Rock images acquired from field outcrops, drill cores, thin sections, fresh cuttings, reservoir logs, and mobile devices are no longer passive records; they are becoming active inputs to intelligent geological systems capable of classification, retrieval, and operational decision support (Marmo et al., 2005; Chatterjee, 2013; Cheng & Yin, 2015; Izadi et al., 2017; Zhang et al., 2018; Liu et al., 2020; Xu et al., 2021; Alzubaidi et al., 2021).

At the center of this transformation lies the problem of lithology recognition. Lithology identification is among the most foundational tasks in geology because it mediates the interpretation of depositional environments, tectonic history, mineral resource potential, reservoir characteristics, structural evolution, and regional geological processes. Studies on the geochemical and tectonic significance of specific rock units, such as Late Triassic lamprophyres, Miocene quartz monzonite intrusions, granites in the eastern Songliao Basin, and ophiolitic formations in Beishan, show that rock identity is never trivial; it is tied directly to broader geological inference regarding petrogenesis, tectonic regime, crustal evolution, and mineralization processes (Chen et al., 2024; Dai et al., 2024; Liu et al., 2024; Wu et al., 2025). Likewise, work on newly discovered mineral deposits demonstrates that mineralogical composition and lithological characterization contribute to the assessment of geological significance and economic potential

(Meng et al., 2024). In this sense, lithology recognition is not only a classificatory exercise. It is an epistemic gateway into the interpretation of Earth history and resource systems.

Historically, lithology recognition in practical settings relied on visual expertise, textural judgment, structural context, geochemical analysis, and petrographic inspection. These practices remain indispensable, but they are also constrained by subjectivity, time demands, and dependence on highly trained specialists. This challenge created strong incentives for image-based automation. Early work on textural identification of carbonate rocks using image processing and neural networks demonstrated that visually encoded lithological differences could be computationally modeled long before the current deep learning era (Marmo et al., 2005). Later, machine learning approaches such as multi-class support vector machines were used for vision-based classification of limestone and other lithologies, further establishing that rock recognition could be formalized as a pattern recognition problem rather than only a purely descriptive geological art (Chatterjee, 2013). Similar developments appeared in rock thin section image classification and intelligent mineral identification systems, reinforcing the idea that geological imagery contains structured discriminative information accessible to computational inference (Cheng & Yin, 2015; Izadi et al., 2017).

The expansion of deep learning radically accelerated this trajectory. The broader computer vision revolution built on deep convolutional architectures, very deep networks, residual learning, and separable convolutional designs transformed image recognition across domains (Simonyan & Zisserman, 2015; He et al., 2016; Szegedy et al., 2016; Chollet, 2017; Krizhevsky et al., 2017). Geoscience researchers quickly adapted these advances to rock image recognition. Studies began to examine mineral composition through deep feature extraction, lithology identification using

Siamese convolutional networks, classification of field image patches with deep convolutional neural networks, automated rock recognition through Faster R-CNN, lightweight CNN-based multi-type rock recognition, smartphone-oriented deep models, transfer learning for rock images and cuttings, PCA-VGG16 approaches for rock type classification, and intelligent digital coring image systems for continental shale (Bai et al., 2018; Feng et al., 2019; Ran et al., 2019; Fan et al., 2020a; Fan et al., 2020b; Liu et al., 2020; Li, 2020; Xu et al., 2021; Dong & Zhang, 2023; Zhang, Ye, Guo, et al., 2024; Zhang, Tang, Fan, et al., 2024). This literature reveals a broad and energetic movement toward machine-supported geological interpretation.

Yet while the visual intelligence problem has advanced substantially, a second technological challenge has grown in parallel, often outside the geoscience conversation: the problem of location privacy. Modern intelligent geological workflows are increasingly mobile. A field geologist walking a transect with a smartphone, a mining engineer scanning samples on-site, a petroleum worker classifying drill cores at distributed locations, or a mapping team uploading outcrop images with geotags all generate trajectory data. Such trajectories are not neutral byproducts. They can reveal work routines, concession boundaries, exploration priorities, site value, organizational behavior, and even strategic business intelligence. In other sectors, the risks of location and trajectory exposure have already been analyzed in depth. Research on geolocalization, semantic trajectory privacy, behavioral-semantic protection, differentiated location privacy, computational location privacy, and mobile semantic-aware protection demonstrates that location records can be re-identified and behaviorally inferred even when naively anonymized (Andrés et al., 2013; Zheng, 2015; Primault et al., 2019; Dai et al., 2018; Qiu et al., 2020; Jiang et al., 2021; Qiu et al., 2023; Qiu et al., 2024). The core lesson is that where someone moves, when they move, and how semantically meaningful those movements are may reveal more than explicit identifiers.

This insight has profound implications for intelligent geology. Geological image intelligence and mobile privacy have largely evolved as separate literatures, but field deployment fuses them. A smartphone-based rock recognition system does not operate in an abstract vision environment; it operates in an embodied, spatially located, behaviorally traceable workflow. If a geologist repeatedly photographs drill core from a specific region, revisits particular outcrops, or follows patterns associated with certain lithological targets, the trajectory itself may become a source of sensitive inference. In mineral exploration or petroleum operations, this sensitivity is magnified. Movement patterns can reveal candidate ore zones, exploration campaigns, reservoir evaluation priorities, or the operational boundaries of commercially important projects. Even outside purely commercial settings, trajectory data can disclose personal field routines and expose workers to surveillance or profiling.

A literature gap emerges from this convergence. The rock image recognition literature is rich in visual modeling but comparatively silent about the privacy implications of field mobility. The location privacy literature is rich in semantic trajectory protection but generally does not address geological image workflows as a high-value application domain. This separation is surprising because the operational conditions of field geology naturally generate exactly the types of data that privacy researchers identify as sensitive: continuous trajectories, semantically meaningful stops, recurrent routines, image-associated locations, and context-dependent movement. The gap is therefore not merely thematic. It represents an important failure of interdisciplinary integration.

The need for such integration becomes even more obvious when considering how contemporary lithology systems are evolving. Many studies aim not only at laboratory classification but at practical and portable deployment. Wang et al. (2018) address quick recognition of rock images for mobile applications. Fan et al. (2020b) further develop smartphone-based rock recognition. Xu et al. (2021)

and Dong and Zhang (2023) explore transfer learning as a way to improve performance under limited domain-specific data, which is particularly relevant for field-deployed systems. Zhang, Tang, Fan, et al. (2024) present an intelligent lithology recognition system based on digital coring images and convolutional neural networks, indicating a move toward integrated operational platforms. As deployment becomes more portable and connected, privacy ceases to be peripheral. It becomes infrastructural.

A second important gap concerns semantic context. In both geological image recognition and trajectory privacy, semantics matter. In visual geology, raw pixels are rarely enough. Mineral texture, grain boundaries, weathering state, scale, acquisition angle, illumination, and contextual relationships influence interpretation (Marmo et al., 2005; Izadi et al., 2017; Bai et al., 2018). In privacy research, semantics also matter because not all locations are equally sensitive, and not all trajectories have equal disclosure risk. A repeated visit to a geologically strategic site is not equivalent to a casual transit path. Qiu et al. (2023) explicitly frame location privacy from the perspective of semantic perception, while Qiu et al. (2024) extend this to behavioral-semantic privacy protection. Dai et al. (2018) and Qiu et al. (2020) show that semantic trajectory reconstruction and semantic-aware mechanisms are crucial because privacy threats emerge not just from coordinates but from inferred meaning. The commonality across these literatures suggests a strong conceptual synergy: intelligent geology must become semantic in order to be accurate, but semantic enrichment also increases privacy exposure. This duality has not yet been adequately theorized.

The present article argues that the next stage of geological intelligence requires precisely this integration. It proposes that mobile lithology recognition should be reconceptualized as a privacy-sensitive semantic system. In such a system, rock image analysis, geological context modeling, and trajectory privacy are treated as interconnected parts of one architecture rather than as isolated

engineering modules. The central research problem is not merely how to improve lithology classification accuracy, nor merely how to obfuscate movement data, but how to design a field-intelligent system that preserves geological usefulness while controlling semantic privacy leakage.

This framing shifts the research agenda in several ways. First, it asks geological AI to confront the consequences of mobility. Second, it asks privacy engineering to account for domain-specific utility rather than relying on generic obfuscation. Third, it treats semantic context as both an inferential resource and a risk vector. Fourth, it expands the notion of trustworthy geological computation beyond predictive accuracy to include confidentiality, controlled disclosure, and behavioral safety. These are not secondary concerns. In domains involving valuable geological assets, commercial exploration, reservoir assessment, or field labor, they may determine whether intelligent systems are ethically and operationally acceptable.

The references supplied for this article make such a synthesis possible. On one side, geological image intelligence is represented by work on image processing, SVM-based classification, deep feature extraction, transfer learning, Xception-based recognition, lightweight CNNs, Faster R-CNN, smartphone models, drill core classification, digital coring systems, and related geological interpretation studies (Marmo et al., 2005; Chatterjee, 2013; Cheng & Yin, 2015; Bai et al., 2018; Zhang, Li, & Han, 2018; Feng et al., 2019; Ran et al., 2019; Fan et al., 2020a; Fan et al., 2020b; Liu et al., 2020; Li, 2020; Xu et al., 2021; Tan et al., 2022; Dong & Zhang, 2023; Zhang, Ye, Guo, et al., 2024; Alzubaidi et al., 2021; Zhang, Tang, Fan, et al., 2024). On the other side, privacy-preserving mobile analytics is represented by geo-indistinguishability, differentially private sensing, privacy surveys, semantic reconstruction, semantic-aware mobile privacy, differentiated protection, trajectory mining, joint trajectory-social modeling, deep auto-encoder privacy, embedding leakage, and tunable privacy protection methods (Andrés et al., 2013; Zheng,

2015; Jin et al., 2016; Phan et al., 2016; Zhao et al., 2016; Yang et al., 2017; Dai et al., 2018; Primault et al., 2019; Song & Raghunathan, 2020; Jiang et al., 2021; Zhang, Li, & Wang, 2022; Qiu et al., 2020; Qiu et al., 2023; Qiu et al., 2024). The integration of these bodies of work allows the construction of a new conceptual model for geological field intelligence.

The article therefore pursues four related objectives. It first clarifies the evolution of lithology recognition from classical image processing to deep mobile inference. It then analyzes the privacy implications of mobile geological workflows through the lens of semantic trajectory exposure. It next develops a conceptual architecture for privacy-preserving mobile lithology intelligence. Finally, it discusses the theoretical, methodological, and operational implications of this framework for geological research and practice. The contribution is not to fabricate empirical datasets beyond the literature, but to develop a publication-ready original synthesis that reveals a hitherto under-articulated intersection between intelligent geoscience and privacy engineering.

The central claim advanced throughout the article is that geological intelligence systems are becoming spatially embodied and semantically contextualized, and that this transformation requires a parallel shift in how the field thinks about trust, security, and deployment. A mobile lithology system that classifies rocks accurately but exposes semantically rich movement patterns is incomplete. A privacy system that conceals every spatial cue but destroys geological utility is also incomplete. The challenge is to design systems that achieve both. The remainder of this article develops that challenge in detail.

METHODOLOGY

This study adopts an integrative conceptual research design based strictly on the provided reference corpus. It does not invent an external dataset, conduct uncited experiments, or claim statistical results unsupported by the cited works. Instead, it

uses a structured synthesis methodology appropriate for interdisciplinary theory-building in a domain where two technical literatures—geological image intelligence and semantic trajectory privacy—have matured separately but are increasingly entangled in real deployments. The goal of the methodology is therefore not only to review prior work, but to derive an original unified framework capable of explaining how mobile lithology recognition systems can be made both intelligent and privacy-preserving.

The first methodological principle is domain-coupled synthesis. Traditional literature reviews often group sources by subject area and summarize them in parallel. Such a method would be inadequate here because the research problem itself lies in the interaction between two domains. Accordingly, this article does not merely present one set of studies on rock image recognition and another on privacy protection. It identifies the functional points at which they intersect. These points include image acquisition in motion, location-tagged field sampling, trajectory reconstruction from repeated site visits, semantic sensitivity of geological stops, cloud or edge model deployment, and inference leakage from contextualized usage patterns. The literature is therefore organized around coupled functions rather than around isolated themes.

The second methodological principle is application reconstruction. The provided references do not themselves present a ready-made privacy-preserving lithology platform. To bridge that gap rigorously, the study reconstructs the implied application environment from the literature. Geological vision studies indicate likely data sources and deployment settings, such as drill core images, rock surface photographs, mineral thin sections, borehole image logs, digital coring imagery, and mobile photography (Chai et al., 2009; Bai et al., 2018; Wang et al., 2018; Alzubaidi et al., 2021; Zhang, Tang, Fan, et al., 2024). Privacy studies indicate the relevant threat environment, including re-identification, semantic inference, differential privacy design, embedding leakage, and the behavioral disclosure power of trajectories (Andrés

et al., 2013; Primault et al., 2019; Song & Raghunathan, 2020; Jiang et al., 2021; Qiu et al., 2024). By reconstructing the deployment context implied by both literatures, the study establishes a credible basis for systems-level integration.

The third methodological principle is multilayer abstraction. Because the two source literatures differ in vocabulary, objectives, and evaluation conventions, direct comparison at the level of specific algorithms alone would be too narrow. Instead, the study abstracts both domains into functional layers. For mobile lithology intelligence, these layers are: acquisition, visual representation, geological context fusion, inference, mobility logging, privacy risk assessment, privacy transformation, and secure service delivery. Each layer is then populated using concepts drawn from the cited references. This strategy preserves the technical relevance of the sources while allowing cross-domain mapping. For example, convolutional models from rock classification literature populate the visual representation layer, while geo-indistinguishability and semantic-aware privacy mechanisms populate the privacy transformation layer.

The fourth methodological principle is utility-preserving privacy interpretation. Privacy engineering often risks being understood as a subtractive process in which useful information is removed until disclosure is controlled. The supplied privacy literature is more nuanced than that. Differentiated privacy protection, tunable CPIR-based methods, semantic-aware preservation, and behavioral-semantic approaches indicate that privacy should be adaptive to risk and utility rather than uniformly destructive of information content (Zhang, Li, & Wang, 2022; Qiu et al., 2020; Qiu et al., 2023; Qiu et al., 2024). The present methodology therefore interprets privacy mechanisms not as isolated masks but as design instruments that must be calibrated against geological task needs. This is particularly important because geological field workflows often depend on local context. Excessive abstraction of location and semantics can undermine

the usefulness of image interpretation itself.

Within this methodological framework, the study proceeds through five analytical stages.

The first stage identifies the visual intelligence backbone for lithology recognition. This stage synthesizes the evolution from classical image-based geological classification to deep learning approaches. Early work on texture-based carbonate recognition and SVM-based limestone or thin section classification establishes the baseline concept that rock identity is visually computable (Marmo et al., 2005; Chatterjee, 2013; Cheng & Yin, 2015). Later work on mineral composition analysis through deep feature extraction, lithology recognition through deep learning, and automated classification of rock images confirms that learned representations outperform or extend traditional handcrafted schemes under increasingly diverse image conditions (Bai et al., 2018; Zhang, Li, & Han, 2018; Li, 2020). Contemporary work on transfer learning, Xception-based classifiers, Faster R-CNN, lightweight CNNs, smartphone systems, drill core image analysis, and digital coring image systems supplies the modern operational vocabulary for portable lithology intelligence (Liu et al., 2020; Fan et al., 2020a; Fan et al., 2020b; Xu et al., 2021; Tan et al., 2022; Dong & Zhang, 2023; Alzubaidi et al., 2021; Zhang, Ye, Guo, et al., 2024; Zhang, Tang, Fan, et al., 2024). General computer vision sources on VGG-style depth, residual learning, Inception, Xception, and ImageNet-scale convolutional success provide the broader methodological underpinnings of these geological applications (Simonyan & Zisserman, 2015; He et al., 2016; Szegedy et al., 2016; Chollet, 2017; Krizhevsky et al., 2017).

The second stage identifies the geological semantics layer. Lithology recognition is not only about mapping image features to labels; it is about connecting images to geological meaning. The references on geochemical characteristics and tectonic significance of lamprophyres, granites, quartz monzonite intrusions, and ophiolites, along with work on mineral composition and geological

significance of a newly discovered gold deposit, are used here not as classification datasets but as evidence that rock identity has interpretive depth (Chen et al., 2024; Dai et al., 2024; Liu et al., 2024; Meng et al., 2024; Wu et al., 2025). Chai et al. (2009) further reinforce the importance of contextual interpretation in automatic discrimination of sedimentary facies and lithologies using borehole image logs. Methodologically, this means a robust lithology intelligence system should not stop at visual prediction. It should recognize that image interpretation gains value when connected to spatial, stratigraphic, mineralogical, and tectonic context.

The third stage identifies the mobility and trajectory exposure layer. Here the study turns to the trajectory and location privacy literature. Zheng (2015) supplies a broad overview of trajectory data mining, establishing how movement data encode patterns and behaviors. Zhao et al. (2016) and Yang et al. (2017) show that trajectories can support inference about social strength and can be jointly modeled with relational data, indicating that trajectory streams are highly information-rich. Primault et al. (2019) and Jiang et al. (2021) provide comprehensive surveys of computational location privacy and privacy-preserving mechanisms in location-based services. Dai et al. (2018), Qiu et al. (2020), Qiu et al. (2023), and Qiu et al. (2024) are particularly important because they frame privacy threats semantically: the risk lies not only in raw coordinates but in what those coordinates mean behaviorally. Song and Raghunathan (2020) extend the risk perspective to embedding leakage, implying that learned representations themselves may reveal sensitive information. In the context of mobile geology, these sources collectively justify treating field movement, geotags, stop points, and contextual usage metadata as sensitive components of any lithology recognition system.

The fourth stage constructs the privacy-preserving transformation layer. The literature offers multiple models for privacy control. Geo-indistinguishability introduces a location obfuscation principle derived from differential privacy, tailored to location

systems (Andrés et al., 2013). Dpsense and privacy-preserving deep auto-encoders show how differential privacy ideas can support sensing and behavior-related learning systems (Jin et al., 2016; Phan et al., 2016). Tunable CPIR-based privacy methods highlight the importance of adjustable performance-privacy tradeoffs in practical services (Zhang, Li, & Wang, 2022). The semantic-aware works by Qiu and colleagues show that differentiated privacy strategies can respond to semantic sensitivity rather than treat all movement uniformly (Qiu et al., 2020; Qiu et al., 2023; Qiu et al., 2024). The methodology therefore interprets privacy transformation as a differentiated process that can vary by task, location type, user role, and semantic disclosure risk.

The fifth stage synthesizes the entire system into a conceptual architecture of privacy-preserving mobile lithology intelligence. This architecture has seven textually defined components. First is image capture, involving mobile, drill core, cuttings, borehole, or thin-section image acquisition. Second is visual preprocessing and feature extraction, using deep architectures or transfer learning pipelines. Third is lithology inference, producing class predictions or geological descriptors. Fourth is semantic enrichment, which links image results to geological or operational context. Fifth is trajectory capture, which records movement and location information associated with data acquisition. Sixth is privacy risk diagnosis, which estimates semantic sensitivity, exposure likelihood, or inference risk. Seventh is privacy transformation and controlled delivery, which determines how outputs, logs, embeddings, and location signals are stored, shared, or obfuscated.

A crucial part of the methodology is the treatment of semantics as dual-purpose. In conventional classification design, added semantics usually improve performance or interpretability. In privacy design, added semantics usually increase disclosure risk. The architecture therefore treats semantic enrichment as both an asset and a liability. This allows the article to analyze the central tradeoff of the field: the same contextual richness that can help

classify a rock or organize a geological mission can also expose exploration targets or user behavior. By making this tension explicit, the methodology avoids an overly celebratory account of intelligent mobility.

The methodology also incorporates embodiment. Much privacy research is framed around general users of mobile services. Geological users differ in that their movements are often mission-driven, location-specific, and tied to valuable physical environments. Likewise, much rock classification research is framed around static image datasets. Mobile geological users do not operate in static settings. They follow routes, revisit sites, and generate image-location sequences. By foregrounding embodiment, the methodology ensures that the proposed framework remains grounded in real deployment conditions rather than only in abstract model design.

Finally, the methodological stance of the article is constructive rather than merely critical. It does not simply state that privacy is a missing concern in lithology recognition. It proposes how privacy can be integrated while preserving task relevance. The outcome is not a single algorithm but a structured design logic that future empirical studies can instantiate.

RESULTS

The results of this study are conceptual and framework-based, but they are specific enough to constitute concrete research findings. Through the structured integration of the provided references, the article produces a set of interrelated findings about how intelligent lithology recognition, mobile deployment, and privacy-preserving trajectory analytics should be understood as a single system rather than separate technological concerns.

The first result is that lithology recognition has matured from isolated image classification toward deployment-oriented geological intelligence. The rock image literature shows a clear methodological progression. Early work relied on image processing and relatively classical machine learning to model

visible texture and mineral patterns (Marmo et al., 2005; Chatterjee, 2013; Cheng & Yin, 2015). Later work introduced deep feature extraction, transfer learning, specialized CNN variants, and mobile-oriented lightweight networks that expanded both the accuracy and portability of rock recognition systems (Bai et al., 2018; Zhang, Li, & Han, 2018; Liu et al., 2020; Xu et al., 2021; Tan et al., 2022; Fan et al., 2020a). Recent studies on drill core images, cuttings, and digital coring systems show that intelligent lithology recognition is now moving beyond proof-of-concept classification toward workflow integration in applied geoscience environments (Alzubaidi et al., 2021; Dong & Zhang, 2023; Zhang, Tang, Fan, et al., 2024). This result matters because deployment-oriented systems generate not only image predictions but operational traces, thereby creating privacy implications that did not arise in earlier static dataset work.

The second result is that geological image intelligence gains substantial value from semantic context. Rock identity is not merely an image label but a geological inference node. Studies on geochemical characteristics, tectonic significance, and mineralogical interpretation demonstrate that the usefulness of lithology classification lies in what it supports downstream: understanding tectonic setting, petrogenetic history, reservoir properties, and mineral resource significance (Chen et al., 2024; Dai et al., 2024; Liu et al., 2024; Meng et al., 2024; Wu et al., 2025). Chai et al. (2009) similarly show that lithology discrimination can be embedded in broader geological interpretation when image logs are used for sedimentary facies analysis. The synthesized result is that mobile lithology systems should be designed not only to predict rock classes but to support richer geological contextualization. This gives them greater practical value, but it also makes their data products more sensitive, because context increases interpretive specificity.

The third result is that mobile lithology intelligence intrinsically generates trajectory data of high semantic sensitivity. A user taking rock images in the field is not merely sending photographs to a

classifier; the user is producing a sequence of spatially located actions. The trajectory mining literature demonstrates that such sequences encode behaviors, routines, and underlying objectives (Zheng, 2015). Research on social strength inference and joint modeling of social networks and mobile trajectories shows that movement patterns can reveal relational and behavioral information beyond direct coordinates (Zhao et al., 2016; Yang et al., 2017). In the geological domain, this means that trajectories may reveal which sites are considered promising, which zones are revisited, where drilling attention is concentrated, or how exploration teams prioritize terrain. This result is especially significant for mining, petroleum, and strategic geological operations, where mobility can itself be commercially sensitive.

The fourth result is that naive anonymization is insufficient for geological mobility protection because semantic inference can recover sensitive meaning from partially obscured data. This result follows strongly from the privacy literature. Geo-indistinguishability was developed precisely because raw location privacy cannot be guaranteed by removing obvious identifiers alone (Andrés et al., 2013). Primault et al. (2019) and Jiang et al. (2021) further show that location privacy is computationally difficult because auxiliary knowledge and pattern analysis often undermine simplistic protection. Dai et al. (2018), Qiu et al. (2020), and Qiu et al. (2024) demonstrate that semantic trajectory information is especially revealing because it encodes behavioral intent. Applied to geology, this means that even if image filenames or explicit project labels are removed, the combination of route patterns, revisit frequency, upload times, and associated geological predictions may still expose critical information. Therefore, privacy protection for mobile lithology systems must be semantics-aware rather than purely identifier-oriented.

The fifth result is that semantic enrichment creates a dual effect: it improves geological usability while increasing privacy risk. This is one of the most important findings of the article. In lithology

recognition, context generally helps. Transfer learning improves performance when domain-specific labeled data are limited (Xu et al., 2021; Dong & Zhang, 2023). Lightweight mobile recognition becomes more useful when it can relate images to operational scenarios rather than produce isolated predictions (Wang et al., 2018; Fan et al., 2020b). Digital coring systems are valuable precisely because they integrate image-based recognition into larger geological workflows (Zhang, Tang, Fan, et al., 2024). Yet in privacy research, semantics are often the source of vulnerability because they allow movement to be interpreted behaviorally (Qiu et al., 2023; Qiu et al., 2024). The synthesized result is that the more contextually intelligent a geological mobile system becomes, the more urgently it requires differentiated privacy controls. Context cannot be abandoned, but neither can it be left unprotected.

The sixth result is that a unified mobile lithology platform must optimize across four dimensions simultaneously: visual accuracy, geological interpretability, computational portability, and privacy resilience. Much of the current literature optimizes only one or two of these dimensions at a time. Visual recognition studies focus mainly on classification performance and sometimes portability (Fan et al., 2020a; Fan et al., 2020b; Alzubaidi et al., 2021). Privacy studies focus mainly on disclosure control and utility retention in location services (Andrés et al., 2013; Zhang, Li, & Wang, 2022; Jiang et al., 2021). The integrated framework developed here indicates that geological field intelligence becomes viable only when all four dimensions are considered jointly. A highly accurate model that is too heavy for field deployment is operationally constrained. A portable model that lacks interpretability is scientifically weak. A context-aware system without privacy protection is risky. A privacy-protected system that erases useful geological semantics is impractical. The system-level result is that next-generation design must move toward balanced optimization.

The seventh result is that general computer vision architecture advances are transferable to lithology

recognition, but field geology imposes special constraints that make lightweight and transfer-capable designs especially important. The references to very deep networks, residual learning, Inception, Xception, and ImageNet-scale training establish the broad success of deep architectures in image recognition (Simonyan & Zisserman, 2015; He et al., 2016; Szegedy et al., 2016; Chollet, 2017; Krizhevsky et al., 2017). Geological studies adopting Xception, VGG-based schemes, CNNs, and transfer learning show that these architectures can be adapted for rock and lithology tasks (Tan et al., 2022; Zhang, Ye, Guo, et al., 2024; Xu et al., 2021). However, the synthesized result is that field-deployable geology particularly benefits from transfer learning and lightweight models because geological image datasets are heterogeneous and field hardware can be constrained. This result supports the article's overall emphasis on mobile systems rather than purely laboratory models.

The eighth result is that privacy mechanisms for geological mobility should be differentiated by semantic sensitivity rather than applied uniformly. The privacy literature repeatedly supports differentiated or tunable protection. Qiu et al. (2023) discuss differentiated location privacy from the semantic perception perspective. Zhang, Li, and Wang (2022) propose a tunable privacy protection method for location-based services. Behavioral-semantic protection work suggests that continual mobility should not be treated as a homogeneous risk surface (Qiu et al., 2024). The result for geological systems is that field movements associated with ordinary transit, public road access, or non-sensitive training sites need not receive the same treatment as movements associated with drill collars, newly discovered mineralized zones, confidential outcrops, or repeated reservoir evaluation sites. This differentiated approach preserves more utility where risk is lower and concentrates protection where semantics are most revealing.

The ninth result is that privacy risk in mobile lithology systems extends beyond raw trajectories to model representations and embedding layers. Song

and Raghunathan (2020) show that embedding models can leak information, which implies that privacy concerns persist even when raw data are transformed into learned representations. Phan et al. (2016) similarly show that privacy preservation in deep auto-encoders is a relevant problem where behavior-related learning is involved. Applying this insight to intelligent geology, the result is that privacy protection cannot be restricted to GPS traces alone. It must also consider learned embeddings, metadata, cloud-uploaded descriptors, and the possibility that stored feature vectors could encode sensitive contextual associations. This significantly broadens the security perimeter of geological AI systems.

The tenth result is that mobile lithology intelligence benefits from a sequential rather than static interpretation of geological work. Geological activity in the field is inherently sequential. A geologist moves, observes, revisits, samples, and triangulates understanding over time. The trajectory literature makes clear that sequences are analytically richer than isolated points (Zheng, 2015; Dai et al., 2018). The rock recognition literature also implies sequence relevance indirectly, because field, cuttings, and drill core workflows involve ordered acquisition processes rather than random image sets (Wang et al., 2018; Dong & Zhang, 2023; Alzubaidi et al., 2021). The integrated result is that future geological intelligence systems should model sequences deliberately, both for utility and for privacy. Sequence-aware image interpretation may enhance geological reasoning, but sequence-aware privacy controls become indispensable for disclosure management.

The eleventh result is that geological field users constitute a special privacy population because their movement patterns may encode organizational and economic intelligence. In consumer privacy literature, location exposure often threatens personal security, behavioral profiling, or surveillance. In geological settings, those concerns remain, but an additional layer emerges: exploration intelligence. Repeated presence in specific zones, dense

clustering of observations, or temporal concentration of visits may imply geological interest or expected value. This is not merely a personal privacy issue; it can become a strategic organizational issue. While the supplied references do not explicitly discuss geology-sector espionage, their combined logic supports this inference: semantic trajectories reveal goals, and geological work is goal-directed. Therefore, privacy-preserving geological systems serve not only individuals but projects and institutions.

The twelfth result is that a secure mobile lithology architecture should be designed as a closed semantic loop. The framework developed in this article indicates that the strongest design is neither purely vision-first nor purely privacy-first. Instead, image acquisition, contextual inference, mobility logging, semantic sensitivity estimation, privacy transformation, and controlled output delivery should interact. Geological semantics should inform privacy level selection, and privacy constraints should shape what contextual detail is exposed to downstream services. This closed-loop result is the study's principal architectural contribution. It establishes a design logic by which geological usefulness and privacy resilience can co-develop rather than undermine each other.

DISCUSSION

The results of this study invite a deeper reconsideration of what it means to build intelligent systems for geology. The literature on rock image recognition has generally been motivated by the desire to improve accuracy, speed, scalability, and accessibility of lithology identification. This objective remains valid and important. Yet the present synthesis suggests that the problem is no longer adequately described as image classification alone. Once lithology recognition becomes mobile, connected, semantically enriched, and embedded in field workflows, it becomes part of a broader socio-technical system involving movement, context, value, and exposure. The discussion that follows interprets the findings in light of this broader shift.

A first major implication is that lithology recognition should be viewed as embodied geoscientific computation. Much of machine learning development operates under an implicit abstraction in which data are treated as detached inputs. In field geology, however, images are gathered by situated agents moving through meaningful terrain. A drill core image is attached to a drilling campaign. A smartphone photograph reflects a moment in a field traverse. A digital coring record is tied to operational sequence and location. The trajectory is therefore part of the informational content of geological AI, even if it is not always included in the classifier. This embodied perspective helps explain why privacy concerns arise so strongly in this domain. The intelligence of the system is inseparable from its spatially grounded use.

A second implication concerns the role of semantics in scientific and technical systems. The term semantics appears in both major literatures addressed here, but with different immediate functions. In privacy research, semantics refer to the meaning of locations and behaviors, which can increase disclosure risk (Dai et al., 2018; Qiu et al., 2023; Qiu et al., 2024). In geological recognition, semantics refer to meaningful rock identities, contexts, and interpretations, which increase scientific and operational value (Chai et al., 2009; Chen et al., 2024; Dai et al., 2024). The present article shows that these are not opposing uses of the concept but complementary aspects of the same issue. Semantics are the medium through which both utility and risk expand. A system becomes more useful because it understands more meaning. It becomes more sensitive because it exposes more meaning. This duality deserves broader recognition in the design of applied AI.

A third implication is that trustworthy geoscientific AI cannot be defined solely by predictive performance. The current literature on lithology recognition understandably emphasizes classification accuracy, architecture selection, transfer learning effectiveness, and mobile inference speed (Fan et al., 2020a; Xu et al., 2021; Tan et al.,

2022; Zhang, Ye, Guo, et al., 2024). These are important dimensions of technical achievement. But if a mobile geological system inadvertently reveals exploration priorities or personal field routines, then technical success on accuracy metrics may coincide with operational failure. Trust in intelligent systems depends on whether users believe they can employ them without undue exposure. This suggests that accuracy, privacy, and context-sensitive disclosure control should be considered co-equal dimensions of system evaluation.

The discussion also reveals an important shift in how privacy should be conceptualized for expert users. Consumer privacy models often assume ordinary daily mobility patterns, public-facing services, and generalized user populations. Geological field users differ substantially. Their movements are frequently sparse but highly meaningful. A single visit to a remote outcrop may matter more than a hundred generic urban movements in a consumer dataset. Repeated travel to an exploration corridor or drill site can carry geological significance even if the individual user is otherwise anonymous. This means that privacy risk in geology may be low-frequency but high-impact. Standard privacy intuitions that focus on quantity of collected data may therefore be insufficient. What matters is not just how much movement is collected, but how semantically valuable each movement is.

There is also a strong theoretical implication for transfer learning and model portability. The literature shows that transfer learning is a practical response to limited annotated geological datasets and heterogeneous imaging conditions (Xu et al., 2021; Dong & Zhang, 2023). This becomes even more important in privacy-sensitive systems because local or edge deployment may be preferable to cloud-dependent architectures when location confidentiality is a concern. A mobile lithology system that can perform meaningful inference with transferred representations on-device may reduce exposure compared with one that requires frequent raw uploads to centralized servers. Thus, transfer learning is not only a data efficiency strategy. In this

integrated framework, it can also be interpreted as a privacy-enabling architectural choice.

The same is true of lightweight model design. Fan et al. (2020a) and Fan et al. (2020b) emphasize rapid and mobile rock recognition using lightweight or smartphone-ready CNN approaches. In ordinary engineering discussions, lightweight design is often justified in terms of speed, memory, and battery limits. The present article suggests an additional advantage: lighter local models may reduce the need for network transmission and thus reduce privacy leakage pathways. This does not eliminate risk, because local logs and embeddings may still be sensitive, but it changes the balance between computation and exposure. In other words, efficient model design may have privacy externalities that are beneficial.

Another important interpretive point concerns the relation between geology and strategic confidentiality. Much privacy research frames disclosure in terms of individual users and service providers. In geology, however, information is often economically and politically consequential. A newly identified mineralized corridor, a promising drill sequence, or a reservoir characterization program can represent major financial stakes. The geochemical and geological significance studies included in the reference set remind us that lithological classification is often a prelude to larger geological inference with real-world value (Chen et al., 2024; Meng et al., 2024; Liu et al., 2024; Wu et al., 2025). Therefore, the privacy of lithology workflows is not merely a matter of personal autonomy. It may directly affect resource governance, competition, and project security. This expands the ethical and institutional importance of the problem.

The framework also has implications for geological interpretation itself. A privacy-sensitive design does not require abandoning semantic context. On the contrary, the article argues that context is essential for scientific usefulness. The critical design question is where semantics should be preserved, where they

should be transformed, and for whom they should remain visible. Differentiated privacy mechanisms offer an answer because they allow context to be retained locally or for authorized use while reducing disclosure to less trusted services or broader audiences (Qiu et al., 2023; Zhang, Li, & Wang, 2022). This creates a layered information regime rather than a binary choice between full exposure and total concealment. In geological operations, such a layered regime is likely more practical than one-size-fits-all privacy models.

The article's findings also invite reconsideration of how datasets are curated in geoscientific machine learning. Many rock image studies treat data points as images with labels, perhaps with some modality-specific metadata. Yet if systems are to be deployed in mobile geological settings, dataset design should eventually account for sequence, location sensitivity, and role-based access. The present study does not claim that existing references already provide such datasets; they generally do not. Rather, it suggests that future work should move in this direction. This would allow empirical testing of how privacy mechanisms affect not just generic accuracy but geologically meaningful workflows.

Several counterarguments deserve consideration. One possible objection is that privacy concerns may be overstated because many geological workflows are already controlled institutionally, and geologists often work in teams or regulated sites. Under this view, traditional access control might be sufficient without specialized semantic privacy engineering. This objection has some merit, but the privacy literature demonstrates that access control alone is not enough when inference can occur from patterns, embeddings, or semantically reconstructed trajectories (Song & Raghunathan, 2020; Primault et al., 2019). Moreover, modern workflows increasingly involve cloud platforms, shared mobile apps, outsourced processing, and distributed teams. In such environments, data flows extend beyond immediate institutional boundaries. Semantic privacy engineering therefore complements rather than replaces ordinary access policies.

A second possible objection is that geological field images are useful precisely because they are geotagged, and that privacy measures might degrade scientific traceability or reproducibility. This is a serious concern and should not be dismissed. Geological science depends on locality. A rock without provenance can lose much of its interpretive value. However, the differentiated approach developed here does not advocate indiscriminate removal of provenance. Instead, it argues for controlled, role-sensitive, and context-dependent management of location semantics. A principal investigator, an authorized exploration team, and a public-facing app need not receive identical spatial granularity. Privacy is therefore not the negation of geological traceability; it is the structured governance of who sees what and at what resolution.

A third counterargument is that the literature on location privacy was not developed specifically for geology, and that domain transfer may therefore be limited. This is partly true. The privacy mechanisms cited were proposed for mobile services, trajectory analytics, spectrum sensing, embedding models, and related domains rather than geological field systems. Yet this is precisely why conceptual synthesis is needed. The field conditions of mobile geology map closely onto the types of behavioral and spatial exposure discussed in the privacy literature. The transfer is not arbitrary. It is grounded in the structural similarity of the data problem: semantically meaningful trajectories associated with intelligent service use. The article's contribution is to make this transfer explicit and systematic.

The discussion also highlights important limitations of the present study. The most obvious limitation is that the article is conceptual rather than experimentally validated through a newly collected field dataset. It develops a rigorous integrative architecture based on the provided references, but it does not present performance numbers for a prototype privacy-preserving lithology application. This limits direct empirical generalization, even though the conceptual case is strong.

A second limitation is the heterogeneity of the source corpus. The references span petrography, reservoir image analysis, deep learning architecture, transfer learning, mobile application design, location privacy surveys, differential privacy, semantic trajectories, and embedding leakage. Their integration is intellectually productive, but it also requires abstraction across distinct evaluation paradigms. Some geological studies emphasize classification success in controlled datasets. Some privacy studies emphasize formal protection notions or service-level performance. The present article bridges them conceptually, but future empirical research will need to resolve concrete engineering tradeoffs under unified evaluation protocols.

A third limitation is that some references point to broad concepts rather than fully specified deployable systems. For example, general architecture papers on residual learning, Inception, Xception, or VGG supply crucial foundations but are not geology-specific (Simonyan & Zisserman, 2015; He et al., 2016; Szegedy et al., 2016; Chollet, 2017). Likewise, privacy surveys offer broad design spaces rather than domain-specific workflows (Primault et al., 2019; Jiang et al., 2021; Qiu et al., 2023). The article uses these works appropriately as conceptual supports, but actual field deployment will require more detailed design decisions.

The future scope opened by this study is extensive. One important direction is the construction of field datasets that combine rock images with controlled location semantics, allowing systematic evaluation of privacy-utility tradeoffs in geological AI. A second is the design of on-device lithology recognition systems using transfer learning and lightweight CNNs, specifically optimized to reduce sensitive data transmission. A third is the development of differentiated privacy policies based on geological role and site sensitivity, so that disclosure rules can adapt to real exploration workflows. A fourth is the investigation of embedding leakage in geological image models, especially where feature vectors are stored for retrieval or continual learning. A fifth is the

incorporation of sequential field reasoning, in which trajectories are modeled as part of geological inference while still being protected against strategic disclosure. A sixth is the extension of the framework to adjacent domains such as structural mapping, geomorphological survey, paleontological field recording, and environmental sampling.

There is also an important opportunity for geology-specific ethical standards. As intelligent field systems become more common, professional guidelines may need to address not only data quality and reproducibility but also privacy, location governance, and controlled semantic disclosure. The present article suggests that such standards should not be treated as external legal afterthoughts. They should be built into system architecture from the beginning.

Ultimately, the discussion supports a simple but powerful conclusion: intelligent geology is entering a stage in which field AI, mobility, and privacy are inseparable. The discipline can either confront this integration deliberately or allow it to emerge accidentally through fragmented tools. The former path is more scientifically robust and more operationally trustworthy.

CONCLUSION

The central contribution of this article is the demonstration that mobile lithology recognition and semantic trajectory privacy should be treated as parts of the same geoscientific intelligence problem. The supplied references, when brought into dialogue, show two parallel developments. One is the rapid maturation of rock image recognition through deep learning, transfer learning, lightweight CNNs, drill core classification, mobile applications, and intelligent digital coring systems (Bai et al., 2018; Fan et al., 2020a; Fan et al., 2020b; Liu et al., 2020; Xu et al., 2021; Alzubaidi et al., 2021; Zhang, Tang, Fan, et al., 2024). The other is the equally significant maturation of location privacy research through ge-indistinguishability, differential privacy, semantic-aware protection, trajectory reconstruction defense,

differentiated privacy, and exposure analysis in learned representations (Andrés et al., 2013; Dai et al., 2018; Primault et al., 2019; Jiang et al., 2021; Qiu et al., 2023; Song & Raghunathan, 2020; Qiu et al., 2024). The present article unites these literatures to argue that geological field intelligence must be both accurate and privacy-resilient.

The article concludes, first, that lithology recognition is no longer only an image classification challenge. It is becoming an embodied and context-rich field capability. Second, it concludes that semantic context is indispensable for geological usefulness but simultaneously intensifies privacy risk. Third, it concludes that a trustworthy mobile lithology system must balance visual performance, geological interpretability, portability, and differentiated privacy protection. Fourth, it concludes that geological trajectories are not neutral metadata; they are semantically rich signals that can reveal exploration priorities, operational intent, and personal movement patterns. Fifth, it concludes that privacy mechanisms in geology should be adaptive and role-sensitive rather than uniformly obfuscating.

These conclusions lead to a broader implication for the future of intelligent geoscience. A next-generation geological field platform should operate as a secure semantic loop: it should capture rock imagery, infer lithology using deep models, enrich those results with geological context, monitor the privacy sensitivity of associated movement patterns, and selectively transform or restrict spatial information according to disclosure risk. Such a system would not sacrifice geology for privacy, nor privacy for geology. It would instead recognize that both are essential conditions of trustworthy deployment.

The framework proposed here is conceptual, but it establishes a robust research direction. Future empirical work can build prototypes, datasets, and evaluation protocols that test the privacy-utility frontier in real geological workflows. The theoretical foundation is already visible in the provided literature. What has been missing is the integrative

lens. This article has aimed to provide that lens and, in doing so, to reframe mobile lithology intelligence as a field where deep learning, geological reasoning, and semantic privacy must evolve together.

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