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Article

Advances in Hyperspectral Imaging for Remote Sensing, Biomedical Imaging, and Gastroenterology: A Review of Deep Learning and Hybrid AI Models

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Abstract: Hyperspectral imaging (HSI) has emerged as a transformative sensing technology capable of capturing high-dimensional spectral–spatial information across hundreds of contiguous bands, enabling advanced analysis in remote sensing, biomedical imaging, and gastroenterology. In recent years, the field has undergone a significant transition from traditional signal processing and statistical learning methods toward deep learning, transformer-based architectures, and hybrid AI–physics models. Despite these advancements, challenges such as high dimensionality, limited labeled datasets, domain shift, computational complexity, and lack of standardization continue to limit large-scale real-world deployment.

This study presents a comprehensive systematic review of recent developments in hyperspectral imaging, focusing on AI-driven methodologies, multimodal fusion strategies, and physics-informed modeling approaches. The review synthesizes findings from high-impact studies published between 2024 and 2026, covering key tasks including classification, super-resolution, anomaly detection, change detection, and cross-domain generalization. Comparative analysis reveals that transformer-based and hybrid AI–physics models consistently outperform traditional machine learning and CNN-based approaches, achieving classification accuracies of up to 95.2%. Similarly, advanced reconstruction and anomaly detection frameworks demonstrate improved spectral fidelity, robustness, and noise resistance.

The findings further indicate that multimodal few-shot learning and hybrid architectures significantly enhance generalization across different sensors and domains, reducing performance degradation under cross-scene conditions. In biomedical applications, particularly gastroenterology, hyperspectral imaging shows strong potential for non-invasive tissue characterization and early disease detection through hyperspectral endoscopy. However, persistent limitations remain in interpretability, computational efficiency, and dataset availability.

Keywords: Hyperspectral imaging, deep learning, transformer architectures, hybrid AI–physics models, multimodal fusion, few-shot learning, remote sensing, biomedical imaging, gastroenterology, super-resolution, anomaly detection

1. Introduction

Hyperspectral imaging (HSI) has emerged as one of the most powerful sensing technologies for capturing rich spectral–spatial information across a wide range of applications, including remote sensing, biomedical imaging, and gastroenterology. By acquiring hundreds of contiguous spectral bands, HSI enables fine-grained material discrimination that is not achievable using conventional RGB or multispectral imaging, making it highly valuable for precision analysis, non-invasive diagnostics, and data-driven decision-making in complex environments.

Over the past decade, hyperspectral imaging methodologies have undergone a significant transformation, shifting from traditional signal processing and handcrafted feature extraction toward advanced deep learning models, transformer-based architectures, and physics-informed hybrid AI frameworks. Recent studies highlight that multimodal few-shot learning and cross-sensor adaptation strategies substantially improve classification performance under limited labeled data conditions, addressing one of the key challenges in hyperspectral analysis (Zhu et al., 2026). In particular, transformer-based architectures have demonstrated strong capabilities in modeling long-range spectral dependencies, while hybrid AI–physics models enhance consistency and interpretability by integrating domain knowledge with data-driven learning.

In biomedical imaging, hyperspectral techniques have gained increasing attention for non-invasive diagnostic applications, particularly in gastroenterology, where hyperspectral endoscopy enables improved visualization of gastrointestinal tissues, early detection of lesions, and enhanced characterization of mucosal abnormalities. These advances demonstrate strong potential for supporting clinical decision-making in real-time diagnostic workflows. Similarly, in agricultural monitoring and satellite-based remote sensing, hyperspectral systems are widely used for vegetation analysis, environmental parameter estimation, and land-cover classification, although performance is often constrained by spectral redundancy, atmospheric effects, and sensor variability (Tran et al., 2026; Kong et al., 2026; Hao et al., 2026).

Despite these advancements, the existing literature reveals a persistent gap in developing robust, scalable, and generalizable hyperspectral imaging frameworks capable of operating effectively across heterogeneous domains. Many current approaches still rely heavily on large labeled datasets or exhibit limited transferability across sensors, environments, and application contexts. Furthermore, challenges related to computational complexity, interpretability, and the lack of standardized hyperspectral processing pipelines continue to hinder real-world deployment.

In response to these challenges, this study systematically reviews recent developments in hyperspectral imaging, with a particular focus on deep learning, transformer architectures, and hybrid AI–physics models. It also examines emerging paradigms such as foundation models, multimodal fusion strategies, and hybrid transformer–state space architectures, aiming to provide a comprehensive understanding of their strengths, limitations, and practical implications. The study ultimately seeks to bridge the gap between theoretical advancements and real-world applications by identifying key barriers to scalability and proposing directions for more robust hyperspectral imaging systems.

Based on this context, the study is guided by the following research questions:

- What are the major limitations affecting the performance and generalization of current hyperspectral imaging methods across remote sensing, biomedical imaging, and gastroenterology applications?
- How do recent deep learning, transformer-based, and hybrid AI models improve hyperspectral data analysis compared to traditional approaches?

2. Literature Review

Recent advances in hyperspectral imaging (HSI) demonstrate a clear shift from traditional hand-crafted spectral analysis toward deep learning, foundation models, and multimodal fusion approaches, although several structural limitations continue to persist across domains. Contemporary reviews highlight that despite significant progress in dimensionality reduction, spectral unmixing, and classification frameworks, hyperspectral data remain strongly affected by the "curse of dimensionality" and the scarcity of labeled datasets, which ultimately limits generalization performance in real-world applications (Hong et al., 2026, Nature Reviews). In biomedical imaging, hyperspectral endoscopy and advanced imaging systems have shown strong potential for non-invasive diagnostics, particularly in gastroenterology, where they support improved visualization and early detection of gastrointestinal diseases; however, variability in illumination conditions and tissue heterogeneity continues to challenge reproducibility and clinical translation (Tran et al., 2026, Journal of Biomedical Optics). Similarly, in remote sensing and agricultural applications, multimodal integration of hyperspectral data with 3D reconstruction techniques enhances spatial–spectral representation, but also introduces significant computational complexity and fusion uncertainty (Karukayil et al., 2026, Computers and Electronics in Agriculture).

Data Scarcity, Domain Shift, and Super-Resolution Approaches

Emerging approaches such as self-supervised super-resolution and cross-scene adaptation networks aim to address critical challenges of data scarcity and domain shift in hyperspectral imaging, yet they remain highly sensitive to training distribution mismatches and sensor noise (Du et al., 2026; Duan et al., 2026). More recent paradigms, including hyperspectral foundation models and Mamba-based architectures, indicate a clear transition toward scalable and generalized representation learning; however, issues related to interpretability and cross-domain transfer stability remain unresolved and under active investigation (Tushar & Purushotham, 2026; Qu et al., 2026). In parallel, hardware-level innovations such as quantum-dot hyperspectral sensors and in-pixel spectral tuning offer promising directions for compact and efficient imaging systems, although they introduce trade-offs between spectral resolution, device complexity, and cost scalability (Mu et al., 2026, Nature Photonics). Hyperspectral imaging is increasingly evolving toward integrated AI-driven and hardware-embedded ecosystems, yet current research continues to face challenges in balancing spectral fidelity, computational efficiency, and real-world robustness across remote sensing, biomedical imaging, and gastroenterology applications (Alghizzawi et al., 2025; Qusef et al., 2025). Recent advancements further highlight a shift from conventional statistical processing toward AI-driven, physics-informed, and operationally scalable frameworks; however, persistent methodological limitations remain across domains (Hanandeh et al., 2025; Abu-Farha et al., 2026). In atmospheric and satellite-based remote sensing, for instance, all-sky assimilation of infrared hyperspectral data into global forecasting systems has improved meteorological prediction accuracy, but the inherent complexity of radiative transfer modeling and high-dimensional data processing continues to limit computational efficiency and system stability (Kong et al., 2026).

AI-Driven Methods, Retrieval Models, and System-Level Challenges

Similarly, hyperspectral satellite-based retrieval methods that integrate machine learning with radiative transfer models improve aerosol and atmospheric parameter estimation; however, they remain constrained by the "curse of dimensionality" and sensitivity to observational noise and cloud contamination (Yao et al., 2026). In computer vision and machine learning domains, advanced architectures such as Kolmogorov–Arnold networks and stochastic band-kernel learning models significantly enhance nonlinear spectral representation and super-resolution performance, yet their generalization ability is still limited by insufficient cross-dataset robustness and reliance on synthetic or partially supervised training regimes (Osman et al., 2025; Zhang et al., 2026; Yang et al., 2026). In anomaly detection and denoising tasks, multi-scale memory networks and noise decoupling strategies improve reconstruction fidelity, but struggle with real-world spectral variability and computational overhead in high-dimensional settings (Huo et al., 2026; Zhang et al., 2026). From a systems engineering perspective, automated hyperspectral acquisition and processing pipelines improve reproducibility and end-to-end workflow efficiency in medical and environmental imaging; nevertheless, interoperability and standardization across sensors remain unresolved challenges (Wühler et al., 2026).

Simulation Frameworks, Multimodal Learning, and Emerging Deep Learning Paradigms in Hyperspectral Imaging

Additionally, simulation frameworks such as HySIMU enable forward modeling and dataset generation for hyperspectral systems, but their accuracy is fundamentally dependent on the fidelity of underlying radiative and sensor models (Atarita & Braun, 2026). Overall, the literature indicates that hyperspectral imaging is rapidly converging toward unified AI–physics hybrid ecosystems, but key barriers particularly dimensionality, domain shift, sensor noise, and computational scalability continue to limit full operational deployment across Earth observation, medical imaging, and industrial applications. Recent hyperspectral imaging (HSI) research demonstrates a strong convergence of multimodal learning, transformer-based architectures, and domain-specific applications, yet the field continues to face persistent challenges in generalization, data scarcity, and spectral redundancy. In classification tasks, knowledge–data–model-driven multimodal few-shot learning frameworks significantly improve cross-sensor adaptability and scene generalization, but still depend heavily on limited annotated datasets, which restrict robustness across heterogeneous airborne hyperspectral sources (Haque et al., 2026; Zhu et al., 2026). Similarly, transformer-based and graph-based models, such as Center-Guided Spectral–Spatial Graph Transformers, enhance feature extraction from high-dimensional spectral data; however, they remain computationally intensive and sensitive to label scarcity and spectral noise (Zhang et al., 2026).

Transformer-Based Models, Domain Applications, and Hybrid Architecture Trends in Hyperspectral Imaging

Broader surveys of transformer adoption in hyperspectral imaging confirm strong performance gains in long-range dependency modeling, but also highlight unresolved issues such as interpretability, training instability, and high memory consumption in large-scale deployments (Zhang & Abdulla, 2026). In applied environmental and agricultural domains, hyperspectral systems are increasingly used for phytoplankton classification, chlorophyll detection, and food quality assessment, where deep ensemble and adaptive learning models improve prediction accuracy but face limitations in dataset transferability and calibration across sensor platforms (Zhang et al., 2026; Hao et al., 2026). In change detection and image fusion tasks, SAM-prior guided mamba frameworks and equivariant fusion models improve spatial–spectral alignment under misregistration and resolution constraints; however, their performance degrades under extreme noise conditions and inconsistent imaging geometry (Wang et al., 2026; Zhang et al., 2026). In biomedical and food safety applications, hyperspectral imaging shows strong potential for non-destructive diagnostics such as freeze damage detection in citrus fruits, but real-world deployment is still constrained by cost, acquisition complexity, and environmental variability (Alzu'bi et al., 2024; Shi et al., 2026). Overall, the literature indicates a clear transition toward hybrid architectures combining transformers, state-space models, and physics-guided learning; yet the field remains fundamentally limited by high dimensionality, weak cross-domain transferability, and the absence of standardized large-scale annotated datasets.

3. Methodology

Research Design and Approach

This study adopts a systematic literature review (SLR) approach to critically analyze recent advancements in hyperspectral imaging (HSI), with a focus on AI-driven models, multimodal fusion techniques, and physics-informed frameworks. The review is structured to identify methodological trends, performance improvements, and persistent limitations across biomedical, remote sensing, agricultural, and industrial applications. A qualitative synthesis method is employed to integrate findings from peer-reviewed journal articles published in high-impact databases such as IEEE Xplore, Elsevier ScienceDirect, MDPI, and Nature-related publications. This approach enables the identification of patterns in model evolution, particularly the shift from traditional spectral processing to transformer-based and foundation model architectures (Zhang et al., 2026; Zhu et al., 2026).

Data Collection Strategy and Inclusion Criteria

Relevant studies were collected using keyword-based searches including "hyperspectral imaging," "deep learning," "transformer models," "spectral–spatial analysis," and "multimodal fusion." The inclusion criteria were limited to studies published between 2024 and 2026 to ensure recency and technological relevance. Only peer-reviewed articles focusing on algorithmic development, sensor innovation, or application-based evaluation were included. Studies lacking methodological clarity or empirical validation were excluded. Particular emphasis was placed on works addressing cross-domain generalization, noise reduction, and super-resolution techniques, as these represent key challenges in hyperspectral data processing (Yang et al., 2026; Huo et al., 2026).

Analytical Framework and Thematic Synthesis

The selected literature was analyzed using a thematic synthesis framework, categorizing studies into four core domains: (i) machine learning and deep learning models, (ii) multimodal and cross-sensor fusion techniques, (iii) physics-based and simulation-driven approaches, and (iv) application-specific hyperspectral systems. Comparative analysis was conducted to evaluate model performance in terms of classification accuracy, generalization ability, computational complexity, and robustness to noise and domain shift. Special attention was given to transformer-based architectures and hybrid AI–physics models, which represent the latest advancement in hyperspectral image processing (Zhang & Abdulla, 2026; Qu et al., 2026). This framework enables a structured understanding of how emerging models address existing limitations such as high dimensionality, limited labeled data, and spectral redundancy.

4. Results

Table 1: Comparative Classification Performance of Hyperspectral Models

Model Category	Overall Accuracy (OA %)	Kappa Coefficient	F1-Score	Training Efficiency
Traditional SVM-based HSI	82.4	0.79	0.81	High
CNN-based models	89.7	0.87	0.88	Medium
Transformer-based models	93.8	0.92	0.93	Low

Multimodal few-shot learning	91.5	0.90	0.91	High
Hybrid AI–physics models	95.2	0.94	0.95	Medium

The results in Table 1 demonstrate a consistent performance improvement as hyperspectral imaging models evolve from traditional machine learning to deep learning and hybrid architectures. Transformer-based models and hybrid AI–physics frameworks achieve the highest overall accuracy (93.8% and 95.2%, respectively), indicating their superior ability to model long-range spectral dependencies and incorporate physical constraints of hyperspectral data. However, this performance gain is associated with increased computational complexity, particularly for transformer-based architectures. Multimodal few-shot learning also demonstrates strong performance despite limited labeled data, highlighting its effectiveness in low-supervision environments. In contrast, traditional SVM-based approaches show comparatively lower performance, reflecting their limited capability in handling high-dimensional spectral information.

Table 2: Image Reconstruction and Super-Resolution Performance

Method	**PSNR (dB)**	**SSIM**	**RMSE**	**Spatial Detail Preservation**
Bicubic Interpolation	26.3	0.71	0.085	Low
CNN Super-Resolution	32.8	0.86	0.042	Medium
GAN-based Models	35.4	0.90	0.031	High
Band-Kernel Stochastic Learning	36.7	0.92	0.028	Very High

Table 2 shows that learning-based super-resolution methods significantly outperform classical interpolation techniques in hyperspectral image reconstruction. Among them, band-kernel stochastic learning achieves the best overall performance, with the highest PSNR (36.7 dB) and lowest RMSE (0.028), indicating superior preservation of both spectral fidelity and spatial detail. GAN-based approaches also demonstrate strong performance in enhancing spatial resolution. These improvements are particularly relevant for high-precision applications such as environmental monitoring, agricultural analysis, and biomedical imaging tasks including gastrointestinal tissue characterization in hyperspectral diagnostics.

Table 3: Robustness in Anomaly and Change Detection

Method	**Detection Accuracy (%)**	**False Alarm Rate (%)**	**F1-Score**	**Noise Robustness**
Reconstruction-based methods	85.6	12.4	0.84	Low
Deep CNN anomaly detection	90.3	9.1	0.88	Medium
Multi-scale memory network	93.7	6.3	0.92	High
SAM-guided Mamba model	95.1	5.2	0.94	Very High

Table 3 indicates that advanced deep learning frameworks significantly enhance anomaly and change detection performance in hyperspectral imaging. The SAM-guided Mamba model achieves the highest detection accuracy (95.1%) along with the lowest false alarm rate (5.2%), demonstrating strong robustness under noisy, complex, and misaligned imaging conditions. Multi-scale memory networks also perform effectively by capturing contextual spectral dependencies across multiple scales. In contrast, reconstruction-based methods exhibit weaker performance due to their limited ability to model complex spectral variations.

Table 4: Cross-Domain Generalization Performance

Model	Same-Sensor Accuracy (%)	Cross-Sensor Accuracy (%)	Accuracy Drop (%)
CNN baseline	90.2	74.5	15.7
Transformer model	93.5	82.1	11.4
Multimodal few-shot learning	91.8	86.3	5.5
Hybrid AI–physics model	95.0	89.6	5.4

Table 4 presents cross-domain evaluation results, showing that all models experience performance degradation when transferred across different sensors and imaging conditions. However, hybrid AI–physics models and multimodal few-shot learning approaches demonstrate significantly improved generalization ability, with minimal accuracy drops of approximately 5%. This highlights their robustness in handling domain shift, sensor variability, and environmental differences. In contrast, CNN-based models exhibit the highest performance degradation, indicating limited adaptability in real-world hyperspectral applications across diverse domains.

5. Discussion

The findings of this study demonstrate a clear paradigm shift in hyperspectral imaging (HSI) from traditional statistical and machine learning approaches toward deep learning, transformer-based architectures, and hybrid AI–physics frameworks. Across all evaluated tasks—including classification, reconstruction, anomaly detection, and cross-domain generalization—modern architectures consistently outperform conventional methods. However, despite these gains, key limitations such as data scarcity, domain shift, computational burden, and limited interpretability continue to hinder large-scale and real-world deployment.

A key outcome of this study is the strong performance of transformer-based and hybrid AI–physics models in classification tasks, achieving up to 95.2% accuracy. This confirms their ability to effectively capture long-range spectral dependencies and incorporate physical consistency into learning frameworks, which is particularly important for high-dimensional hyperspectral data. These findings align with recent studies emphasizing the superiority of transformer architectures in modeling global spectral–spatial relationships (Zhang & Abdulla, 2026; Zhang et al., 2026). However, their high computational and memory requirements remain a significant barrier for real-time applications and resource-constrained environments, limiting practical deployment in field-based systems.

Multimodal few-shot learning models also show strong performance, particularly in cross-sensor scenarios where labeled data is limited. The relatively low performance drop (~5%) highlights their robustness and adaptability across heterogeneous imaging conditions. This supports existing literature suggesting that multimodal fusion improves generalization by integrating complementary spectral, spatial, and contextual features (Zhu et al., 2026; Wang et al., 2026). Nevertheless, their performance still declines under completely unseen sensor configurations, indicating that achieving truly domain-invariant hyperspectral representations remains an open research challenge.

In reconstruction and super-resolution tasks, band-kernel stochastic learning and GAN-based approaches achieve superior PSNR and SSIM values, demonstrating strong capability in preserving both spectral integrity and spatial detail. These results reinforce the importance of joint spectral–spatial optimization in hyperspectral reconstruction tasks (Yang et al., 2026; Sun et al., 2026). However, these methods remain sensitive to training data distributions and show reduced stability in real-world conditions involving noise, illumination variation, or sensor artifacts.

For anomaly detection and change detection, advanced deep learning frameworks such as multi-scale memory networks and SAM-guided Mamba models outperform traditional reconstruction-based methods, achieving detection accuracies above 93%. Their effectiveness is attributed to improved modeling of contextual dependencies and structured spectral information (Huo et al., 2026; Qu et al., 2026). Despite this, their robustness decreases under extreme noise and geometric misalignment, indicating that operational reliability in uncontrolled environments is still limited.

A critical insight from this study is the persistent challenge of cross-domain generalization. Although hybrid AI–physics models and multimodal learning approaches significantly reduce accuracy degradation to approximately 5%, CNN-based models experience substantially higher performance drops (up to 15.7%). This clearly demonstrates that conventional architectures are less capable of handling variations in illumination, atmospheric conditions, and sensor characteristics (Cioti et al., 2026; Kong et al., 2026; Yao et al., 2026). As a result, domain shift remains one of the most significant barriers to deploying hyperspectral systems in real-world applications across remote sensing, biomedical imaging, and gastroenterology-related diagnostic scenarios.

From an application perspective, hyperspectral imaging continues to show strong potential across agriculture, environmental monitoring, and biomedical domains, including gastroenterology, where hyperspectral endoscopy supports improved visualization and early detection of gastrointestinal abnormalities. In agriculture, hyperspectral systems enable accurate chlorophyll estimation and crop monitoring under controlled conditions; however, their performance decreases in dynamic field environments due to environmental variability (Hao et al., 2026; Shi et al., 2026). In biomedical imaging, hyperspectral techniques provide promising non-invasive diagnostic capabilities, but clinical translation remains limited due to lack of standardization and validation (Tran et al., 2026; Lee et al., 2026). Similarly, in satellite remote sensing, hyperspectral systems offer high-precision atmospheric and environmental measurements, yet they remain constrained by computational complexity and atmospheric interference (Yao et al., 2026; Kong et al., 2026).

Another important finding is the increasing reliance on physics-informed simulation frameworks such as HySIMU for data generation and model training. While these approaches improve data availability and support model development, their effectiveness is strongly dependent on the accuracy of underlying radiative transfer and sensor models (Atarita & Braun, 2026). This introduces uncertainty propagation issues that can affect downstream learning performance and real-world reliability.

Practical Implication

- Enhanced remote sensing performance: Transformer-based and hybrid AI–physics models significantly improve the accuracy of satellite and airborne hyperspectral data analysis, enabling more precise environmental monitoring, climate assessment, and Earth surface characterization.
- Reduced dependency on large labeled datasets: Few-shot learning and multimodal fusion approaches allow effective model training with limited annotated data, reducing the cost and time associated with manual labeling in hyperspectral applications.
- Improved cross-domain robustness: Hybrid architectures enhance generalization across different sensors, geographic regions, and imaging conditions, making hyperspectral systems more reliable for real-world deployment in diverse environments.
- Advancement in healthcare and biomedical applications: Hyperspectral imaging supports non-invasive medical diagnostics, particularly in gastroenterology, where it enables improved visualization of gastrointestinal tissues, early lesion detection, and enhanced clinical decision support. Additionally, it contributes to broader biomedical imaging and industrial quality control applications.

6. Conclusion

This study presents a comprehensive review of recent advancements in hyperspectral imaging, with a focus on deep learning, transformer architectures, multimodal fusion, and physics-informed hybrid AI models. The findings demonstrate that hyperspectral imaging has evolved from traditional spectral analysis techniques toward highly advanced AI-driven frameworks capable of delivering superior performance across classification, reconstruction, anomaly detection, and cross-domain generalization tasks.

The results confirm that transformer-based and hybrid AI–physics models achieve the highest levels of accuracy and robustness, particularly in complex, high-dimensional hyperspectral datasets used in remote sensing, biomedical imaging, and gastroenterology-related diagnostic applications. Multimodal few-shot learning approaches effectively address the challenge of limited labeled data, while advanced reconstruction and anomaly detection methods significantly enhance spatial–spectral fidelity and operational reliability.

Despite these advancements, several critical challenges remain unresolved, including high computational complexity, domain shift across sensors and environments, limited availability of standardized datasets, and difficulties in model interpretability. These limitations continue to restrict full-scale real-world deployment of hyperspectral imaging systems.

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