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Editorial

Topical Collection on "Traditional and Machine Learning Methods to Solve Imaging Problems"

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1. Overview of the Topical Collection

Imaging problems, including image reconstruction, restoration, enhancement, segmentation, classification, object detection, and secure image transmission, have traditionally been addressed using analytical methods derived from mathematical models and domain-specific knowledge. Regularization, filtering, optimization, geometric modeling, and statistical estimation remain important because their assumptions and behavior can often be understood and controlled explicitly. More recently, Machine Learning (ML) and Deep Learning (DL) methods have achieved impressive results by learning complex image representations directly from large datasets. Current research increasingly seeks to combine these two perspectives. Instead of treating analytical and learning-based methods as competing alternatives, hybrid approaches incorporate physical constraints, signal-processing principles, or application-specific knowledge into trainable systems. This can improve data efficiency, interpretability, robustness, and computational performance while retaining the representational power of modern neural networks.

The seventeen articles in this Topical Collection reflect this continuing transition. They cover a broad range of research topics and applications, including remote sensing, transportation, medical imaging, agriculture, forestry, cultural heritage, hyperspectral image analysis, image security, and visual storytelling. Collectively, they demonstrate advances in deep architectures, multisensor fusion, hybrid model-based learning, computational efficiency, image-quality assessment, and domain-specific deployment. They also identify recurring challenges related to limited datasets, generalization, robustness, evaluation, and the transfer of experimental methods into real operational environments.

2. Key Findings and Contributions

2.1. Earth Observation, Environmental Monitoring, and Transportation Safety

A substantial group of contributions applies DL to aerial or satellite imagery, road-scene images, and highway videos, supporting applications in environmental monitoring, agriculture and forestry, transportation safety, maritime surveillance, and disaster response. Together, these studies demonstrate the growing importance of automated image interpretation and, in some cases, coordinated Unmanned Aerial Vehicle (UAV) operations to support monitoring and decision-making.

Alkilani et al. (*Contribution* 1) combine UAV coordination with YOLOv8-based human detection for natural-disaster search-and-rescue operations. The detector is pretrained using the VisDrone dataset and refined through data augmentation, while a Jordan-specific UAV dataset provides images from desert, agricultural, industrial, and peri-urban

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environments. Simulations indicate that a cluster of 16 drones could completely survey a 17.6 km² area in less than 40 minutes, compared with an estimated 8.4 hours for a single UAV. The work demonstrates the potential of coordinated autonomous platforms to accelerate emergency searches, although the complete multi-UAV system still requires validation under real flight, communication, and environmental conditions.

Nanni and Brahnam (*Contribution* 2) investigate Local Climate Zone classification using SENTINEL-1 radar and SENTINEL-2 multi-spectral imagery. Because common pretrained networks generally accept only three input channels, the authors create multiple three-channel representations and combine the predictions of models trained on complementary sensor views. Their findings show that multi-spectral and radar information perform substantially better than RGB data alone. Moreover, a relatively simple ensemble of established CNNs can outperform more specialized architectures. The principal drawback is its computational cost, which may prevent direct onboard or edge deployment without model compression or ensemble reduction.

Tan et al. (*Contribution* 4) improve YOLOV5S for detecting road obstacles such as potholes, fallen trees, and stones. Their model introduces multi-scale feature fusion, Efficient Multi-Scale attention, and an improved contextual feature-extraction module. These modifications increase detection performance for objects with different dimensions and appearances. However, overlapping obstacles and complex visual backgrounds still cause errors, indicating a need for improved contextual reasoning and more varied training data.

Zhang et al. (*Contribution* 5) develop a lightweight Transformer for detecting abandoned objects on highways from RGB videos. The architecture combines efficient feature extraction with cross-layer and multi-scale interactions, preserving detailed spatial information while reducing the number of parameters and computational operations. It improves upon the considered baseline model and is designed for real-time surveillance. Nevertheless, the evaluation dataset contains primarily daytime scenes and relatively few examples of nighttime conditions, severe weather, or unusual objects. Broader testing is therefore required before reliable deployment across diverse road environments.

Satlawa and Fisher (*Contribution* 10) formulate forest-thinning assessment as a pixel-level semantic-segmentation task. Their method combines high-resolution RGB and near-infrared orthophotos with canopy height, terrain elevation, and slope information. DEEPLABV3+ with a ResNet-101 backbone produces the best results, achieving a mean F1-score of 82.23% when distinguishing thinning areas, areas not requiring thinning, and non-forest regions. Orthophotos provide most of the useful information, while canopy-height data offer an additional improvement. Predicting the urgency of thinning is considerably more difficult, suggesting that visual and topographical data alone may be insufficient and that forestry variables such as tree age, stand density, and expected yield should also be considered.

Patel et al. (*Contribution* 16) combine graph-neural-network-based feature extraction with YOLOV7 to detect ships in high-resolution synthetic-aperture-radar satellite images. The study supports applications including maritime traffic monitoring, illegal-fishing detection, pollution control, border surveillance, and security. Its experiments also examine the influence of optimization settings and dataset partitions. However, the authors observe that the available dataset should be extended to capture a wider range of ship classes likely to occur in operational maritime monitoring.

Sulemane et al. (*Contribution* 17) evaluate CNN-based detection of gaps in vineyard plantations using UAV images, including multi-spectral information and several color representations. Their results indicate that lightweight architectures can support precision agriculture, with Tiny-YOLOV4 offering the best balance between accuracy and computational requirements for onboard use. The system can identify small gaps and areas with

limited vegetation but may confuse roads or spaces near trees with missing vines. Dataset imbalance and incomplete annotations currently limit fair comparisons among spectral representations and model configurations.

Together, these contributions highlight the value of multisensor information, multi-scale-based feature extraction, and computationally efficient models. At the same time, operational deployment remains constrained by insufficient environmental diversity, incomplete labels, domain shifts, communication requirements, and limited evaluation outside controlled datasets.

2.2. Medical Imaging and Image Reconstruction

The medical and scientific imaging contributions illustrate how preprocessing, model-based reconstruction, learned parameter selection, and rigorous evaluation can complement one another.

Li et al. (*Contribution* 9) introduce a preprocessing pipeline for detecting coronary-artery stenosis, particularly in small branch vessels that are difficult to distinguish in X-ray angiography. Their method combines a Hessian-based Frangi vesselness filter with image fusion. Vessel filtering enhances narrow vascular structures, while fusion preserves information that enhancement might otherwise remove and suppresses false vessel-like patterns produced during enhancement. Testing with five object-detection networks indicates that the preprocessing approach consistently improves stenosis detection. However, the dataset contains only 250 annotated images from 20 patients at a single institution. Broader multicenter studies, additional angiographic views, and prospective clinical validation are therefore required.

Kojima and Yoshinaga (*Contribution* 15) integrate a neural parameter estimator with the two-parameter iterative algorithm, named PDEM, for computed-tomography reconstruction. Instead of manually selecting reconstruction parameters for every scan, the network learns appropriate values directly from noisy projection data and reference images. The training process does not require optimal parameters as labels, which simplifies supervision. Parameters learned using small 64×64 projections also improve the corresponding 128×128 reconstructions, reducing training memory and computational demands. The selected parameters depend on both the projection noise and the shape of the reconstructed object. Although the approach reduces granular noise and improves boundaries, it is evaluated only with simulated Shepp–Logan phantoms, so its effectiveness on clinical CT acquisitions remains unknown.

Wang and Healy (*Contribution* 13) address a different but equally important issue: the objective evaluation of Gibbs-ringing reduction. Gibbs ringing appears near discontinuities when images are reconstructed from incomplete or band-limited Fourier measurements and can affect MRI, digital holography, optical tomography, and other Fourier-based modalities. The authors compare metrics using a synthetic square, a Shepp–Logan phantom, and a real brain MRI slice. Six full-reference metrics (ℓ_0^ϵ, SSIM, MS-SSIM, MAE, Huber loss, and entropy) identify a meaningful balance between ringing suppression and excessive blurring. Restricting evaluation to edge regions does not significantly improve most metrics, suggesting that whole-image measurements are generally adequate. The study also provides guidance on threshold selection for ℓ_0^ϵ and Huber loss.

Taken together, these articles represent three complementary research directions: enhancing clinically relevant structures before learning, using neural networks to control reconstruction algorithms, and developing more reliable criteria for comparing reconstruction results. They also point out that performance improvements alone are insufficient without representative clinical data and evaluation measures linked to perceptual or diagnostic relevance.

2.3. Hyperspectral and Multi-Spectral Imaging

Hyperspectral and multi-spectral imaging capture information across multiple wavelength bands, offering spectral detail that can help distinguish material or biological properties better than conventional RGB imaging. Several papers demonstrate the increasing integration of these data with ML and accessible software environments.

Bakker et al. (*Contribution* 6) present HYPPY, a free and open-source Python package for reading, visualizing, processing, and analyzing hyperspectral imagery. The package provides graphical, command-line, and programmatic interfaces and supports common ENVI formats and spectral libraries. Users can select bands by physical wavelength, automatically sort wavelengths, and exclude unreliable bands. The software supports complete workflows for mineral identification, drill-core analysis, Martian geological mapping, methane-sensor simulation, hyperspectral-camera calibration, research prototyping, and education. Its principal contribution is accessibility and flexibility rather than maximum processing speed, making it particularly valuable for experimentation, teaching, and transparent methodological development.

Pourdarbani et al. (*Contribution* 12) use local spectral-spatial hyperspectral imaging and 3D CNNs to identify early bruising in lemons. Their data contain 174 wavelength bands between 550 and 900 nm, and samples are classified as healthy, eight hours after bruising, or sixteen hours after bruising. By jointly processing the spatial and spectral dimensions, the networks can capture subtle changes not readily visible in standard color images. ResNet achieves the strongest reported classification performance, while alternative networks offer faster processing. The dataset contains only 210 hyperspectral samples and 21 test cases, but augmentation helped the model generalize its predictions.

The studies by Nanni and Brahnam (*Contribution* 2), Satlawa and Fisher (*Contribution* 10), and Sulemane et al. (*Contribution* 17), already discussed in Subsection 2.1, also reinforce the value of non-RGB spectral information. Across these applications, additional spectral channels improve classification or segmentation, but they introduce challenges involving sensor calibration, data dimensionality, computational demands, and limited annotated datasets.

2.4. Image Understanding for Segmentation, Cultural Heritage, and Storytelling

Modern image analysis is expanding beyond detecting isolated objects toward understanding complete scenes, relationships, historical content, and narratives across image collections.

Mohammed and Ralescu (*Contribution* 8) review semantic, instance, and panoptic segmentation. Semantic segmentation assigns a category to every pixel, while instance segmentation distinguishes separate objects belonging to the same category. Panoptic segmentation integrates these objectives by representing both countable "things", such as vehicles and people, and background "stuff", such as roads, vegetation, or sky. The review discusses major neural architectures, relevant datasets, evaluation metrics, industrial systems, and hybrid pipelines in which traditional image processing supports neural-network post-processing. It provides a broad account of the transition from object recognition toward comprehensive scene understanding.

Guidi et al. (*Contribution* 14) apply Mask R-CNN in the open-source computer vision framework DETECTRON2 to segment Egyptian hieroglyphs in RGB photographs of papyrus, stone, pottery, and other historical surfaces. Transfer learning from a model pretrained on COCO produces substantially better masks than training the architecture from scratch, demonstrating the importance of pretrained visual representations when specialist datasets are small. Longer training generally improves segmentation, while lowering the objectness threshold detects more glyphs but also introduces less reliable predictions. Faded, damaged,

low-contrast, and shadow-dependent inscriptions remain difficult, indicating that data augmentation, image enhancement, and larger expert-annotated datasets are required.

Lotfi et al. (*Contribution* 11) review methods for transforming image collections into coherent stories. They propose a unified taxonomy encompassing image curation, preprocessing, information extraction, semantic enrichment, knowledge linking, story modeling, summarization, narrative discovery, generation, presentation, querying, and quality assessment. The review connects computer vision with natural-language processing, reinforcement learning, knowledge graphs, clustering, and visualization. It concludes that existing research generally addresses individual components but does not yet provide mature systems capable of turning large, disconnected image collections into comprehensive, contextual, accurate, and engaging narratives. Existing text-generation metrics also fail to adequately capture creativity, coherence, factual consistency, and audience engagement.

These contributions underscore that image understanding requires contextual and relational knowledge, not visual classification alone. Important open problems include incomplete semantic context, limited domain-specific datasets, unreliable captioning, weak narrative-evaluation measures, and the integration of visual content with language and structured knowledge.

2.5. Image Security, Privacy, and Covert Communication

The Topical Collection also addresses the secure distribution and concealed transmission of visual information, highlighting image quality and robustness in secret-image sharing, and the balance between embedding capacity, visual fidelity, and detectability in steganography.

Huang et al. (*Contribution* 3) propose a robust (k, n)-threshold secret-image-sharing approach in which a secret image is divided among multiple meaningful QR-code shares. Reconstruction requires at least k shares, while fewer shares provide essentially no useful information. The method combines polynomial secret sharing with Reed–Solomon error correction and image inpainting to recover information from noisy or damaged shares. The approach avoids pixel expansion and introduces two variants: G16 generally provides greater speed and overall reconstruction quality, whereas G4 can retain finer details. The method achieves lossless reconstruction under low-density salt-and-pepper noise and remains usable at higher corruption levels. However, the current algorithm offers limited flexibility in choosing the threshold and is barely robust to noise.

Rabie et al. (*Contribution* 7) introduce a high-capacity DCT-based steganographic method that hides a secret image while preserving the appearance and statistical structure of the cover image. Instead of directly replacing high-frequency DCT coefficients, the method models them through polynomial regression. The method then adaptively adds or subtracts scaled secret samples from the modeled coefficients, depending on which operation better matches the original image. A zigzag-scanning variant reduces the additional polynomial information that must be transmitted. The method achieves a competitive balance between embedding capacity and visual quality. A CNN-based steganalysis detector performs at approximately chance level when distinguishing the generated stego images from cover images, whereas conventional coefficient replacement is detected much more reliably. The main trade-off is that more complex polynomial models improve fidelity while increasing communication overhead.

Together, these contributions show that image-security research is progressing beyond basic payload maximization. Contemporary methods must address confidentiality, share recoverability, imperceptibility, robustness to noise, automated steganalysis, and practical storage or transmission constraints.

3. Conclusions

The contributions collected here reflect several developments in imaging research, including the use of complementary sources of information from multiple sensors and modalities. Instead of relying exclusively on RGB images, modern systems increasingly integrate multi-spectral and hyperspectral measurements, radar imagery, elevation data, and spatial, temporal, or contextual information. This complementary information can improve classification, segmentation, reconstruction, and object detection, particularly in complex applications such as environmental monitoring, medical imaging, agriculture, and transportation.

Another recurring theme is combining established image-processing methods with learning-based approaches. Neural networks are increasingly integrated with physical imaging models, signal-processing techniques, iterative reconstruction algorithms, polynomial modeling, image enhancement, and error-correction methods. These hybrid approaches seek to combine the interpretability and constraints of analytical models with the ability of DL to extract complex representations from data. At the architectural level, Transformers, graph neural networks, attention mechanisms, and multi-scale feature-fusion modules are being adapted to imaging problems that require stronger contextual and relational reasoning.

Computational efficiency and real-world deployment are also prominent concerns. Lightweight networks, compact feature extractors, and efficient detection architectures are being designed for UAVs, satellites, roadside systems, and other resource-constrained platforms. Transfer learning has also become especially important in fields where expert-labeled datasets are small or expensive, including medical imaging and cultural heritage. At the same time, researchers are paying greater attention to robustness, image-quality assessment, uncertainty, and resistance to automated attacks. Open-source tools and reproducible processing workflows are further helping to make advanced imaging methods more accessible, transparent, and easier to compare across applications.

Overall, the Topical Collection highlights the complementary roles of traditional and ML-based imaging methods. The most promising direction is not simply replacing analytical algorithms with neural networks. Instead, future imaging systems should combine domain knowledge, physical constraints, diverse data, efficient computation, transparent evaluation, and explicit uncertainty management. Such integration will be essential to turn experimental advances into reliable systems that operate safely and effectively in real-world settings.

4. Future Research Directions

Despite substantial progress, the collected contributions highlight that imaging research still faces limitations in data availability, generalization, robustness, computational efficiency, and evaluation. Many methods are developed using small, geographically restricted, simulated, or incompletely annotated datasets. Strong results under these conditions do not necessarily guarantee reliable performance across different populations, sensors, institutions, environments, or acquisition protocols. Moreover, robustness is often assessed through artificial perturbations rather than realistic combinations of noise, compression, occlusion, weather variation, sensor drift, and communication failures. Large neural networks and ensembles may also be unsuitable for resource-constrained platforms, while conventional performance metrics do not always reflect perceptual quality, diagnostic value, security, or operational usefulness. Questions concerning uncertainty, interpretability, reproducibility, privacy, and failure detection also remain insufficiently addressed.

Future research should focus on developing imaging methods that generalize reliably across different populations, locations, sensors, seasons, and acquisition conditions.

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This will require larger, more diverse datasets; carefully controlled training and testing partitions; consistent annotation standards; and validation across independent institutions and geographical regions. When extensive annotation is impractical, self-supervised, semi-supervised, weakly supervised, and few-shot learning could reduce dependence on costly expert-labeled data.

Another important direction is the closer integration of domain knowledge with data-driven models. Physics-informed and model-guided learning offer ways to incorporate known properties of imaging systems while retaining the flexibility of neural networks. Multimodal approaches could also better exploit complementary spectral, spatial, temporal, textual, clinical, and contextual information, depending on the application. At the same time, models intended for UAVs, satellites, medical devices, and roadside systems should be optimized for limited memory, energy, bandwidth, and processing capacity. Consequently, future evaluations should report latency, computational cost, and resource consumption alongside task-specific performance.

Greater attention should also be devoted to robustness, interpretability, uncertainty estimation, and failure detection. Depending on the application, imaging systems should be tested under realistic noise, compression, occlusion, weather variation, sensor changes, and previously unseen conditions, rather than relying solely on synthetic perturbations. They should provide interpretable outputs where appropriate and indicate when predictions are uncertain or potentially unreliable, especially in safety-critical applications. Further progress would benefit from standardized evaluation protocols that combine quantitative metrics with human or domain-expert assessment, together with open datasets, public implementations, reproducible experiments, independent replication, and prospective testing in real operational environments.

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