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Digital Transformation in National Defense: A Bibliometric Review of Distributed Image Analysis Technology

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Abstract

As remote sensing technology continues to advancing, image analysis systems must efficiently manage substantial volumes of data. The incorporation of deep learning into distributed computing systems has become essential for addressing this demand, facilitating important tasks like object detection and real-time classification. This research methodically outlines the landscape of distributed machine learning for image analysis to pinpoint technological trends that can enhance network-centric imagery intelligence (IMINT). By employing a PRISMA-guided literature review and a bibliometric analysis of 59 publications from Scopus (2015–2026), we chart the field's progression from fundamental distributed computing to optimized, real-time analytical systems. Analyzing keyword co-occurrence and thematic synthesis uncovers significant clusters, including distributed deep learning, privacy-preserving collaboration, and edge-based inference. Based on this examination, we identify and assess key adaptable technologies like split computing, federated learning, and lightweight model optimization for their applicability in operational contexts defined by limited connectivity and decentralized resources. By aligning global research trends with specific national requirements, this review provides a strategic framework for developing resilient, efficient, and adaptive IMINT capabilities within a network-centric paradigm.

Keywords: Deep learning; Distributed System; Image Analysis; IMINT; Network-Centric.

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INTRODUCTION

The advancement of imagery intelligence (IMINT) technologies in recent years has primarily been influenced by studies in remote sensing, environmental monitoring, precision agriculture, and urban surveillance systems. Techniques based on machine learning, particularly Convolutional Neural Network (CNN), have become essential for core tasks such as object detection and image classification due to their superior capability in extracting hierarchical spatial features from complex geospatial datasets (X. Chen et al., 2025). Even with the arrival of newer models such as Transformers, CNN continue to be a leading and practically advantageous option for distributed IMINT systems. Their established architecture, thorough optimizations for parallel and edge processing, and clear understanding of the compromises among accuracy, latency, and resource use render them exceptionally appropriate for incorporation into operational frameworks that are resource-limited and network-centric (He et al., 2016; Howard et al., 2017).

Emerging computational paradigms such as distributed computing architectures, edge AI, and federated learning are increasingly being designed and optimized around CNN-based workflows to enable rapid, resource-efficient, and decentralized analysis (J. Chen & Ran, 2019; Liu et al., 2024). This research path corresponds with the essential requirement to improve IMINT systems in a network-centric operational framework, which necessitates strong, adaptable, and scalable analytical abilities, even in the face of considerable computational and infrastructural limitations (Gomes et al., 2025).

These technical specifications are particularly important in the present landscape of Indonesian defense system. Adityayuda et al. (2024) points out that while advanced technologies like Artificial Intelligence (AI), radar, and CCTV can greatly enhance detection abilities, issues such as inconsistent infrastructure and the preparedness of human resources continue to be significant hurdles in establishing effective remote sensing systems for detecting potential threats in border regions. The dependability of a national surveillance system relies not just on advanced algorithms, but also on a strong basis of digital infrastructure and secure communication (Zwane et al., 2018).

Consequently, incorporating the technical concepts discussed such as a robust edge-cloud infrastructure, privacy-focused collaborative learning, and a streamlined and effective computing model could be a practical approach to enhancing Indonesia's IMINT framework. These strategies are specifically designed to provide high-fidelity analytical capabilities within environments characterized by heterogeneous connectivity, limited bandwidth, and decentralized resources (Atre et al., 2021). By implementing and customizing such frameworks, Indonesia can strategically

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avoid the necessity for large-scale, expensive infrastructure deployments. Instead, it can develop a resilient, scalable, and network-centric IMINT ecosystem that remains operationally effective even in remote or infrastructure-sparse border areas.

The shift to these resilient systems, however, necessitates a thorough comprehension of the technologies that are best suited to these operational limitations, a topic that is still infrequently covered in recent IMINT literature reviews. Given this context, this article presents an extensive review utilizing bibliometric analysis of machine learning-driven image analysis in distributed systems. Through keyword co-occurrence analysis and thematic investigation of existing literature, this research aims to:

1. Identify significant research trends and clusters in distributed image analysis.
2. Highlight key architectures and methods that are best suited for adaptation to improve network-centric IMINT capabilities in Indonesia.

METHODOLOGY

This review follows the PRISMA guidelines to maintain a systematic and reproducible approach Moher et al. (2010) using the search parameters and inclusion criteria shown in Fig 1. The preliminary search produced 68 results. Research papers that focused solely on improving algorithms without offering system-level insights were excluded. As a result, the final review contains 59 publications. The titles and abstracts were assessed according to the specified inclusion criteria:

1. The primary focus is on distributed, decentralized, or federated architectures for image analysis and machine learning.
2. Attention is given to architectural design, optimization, scalability, and real-time processing capabilities.
3. Applications explored include geospatial information, remote sensing, and surveillance contexts.

Focusing on decentralized architectures is essential for managing national infrastructure challenges, such as limited connectivity and scattered data sources. By narrowing the scope to remote sensing and surveillance, this synthesis provides a practical framework to adapt global technological trends into efficient, and scalable imagery intelligence capabilities.

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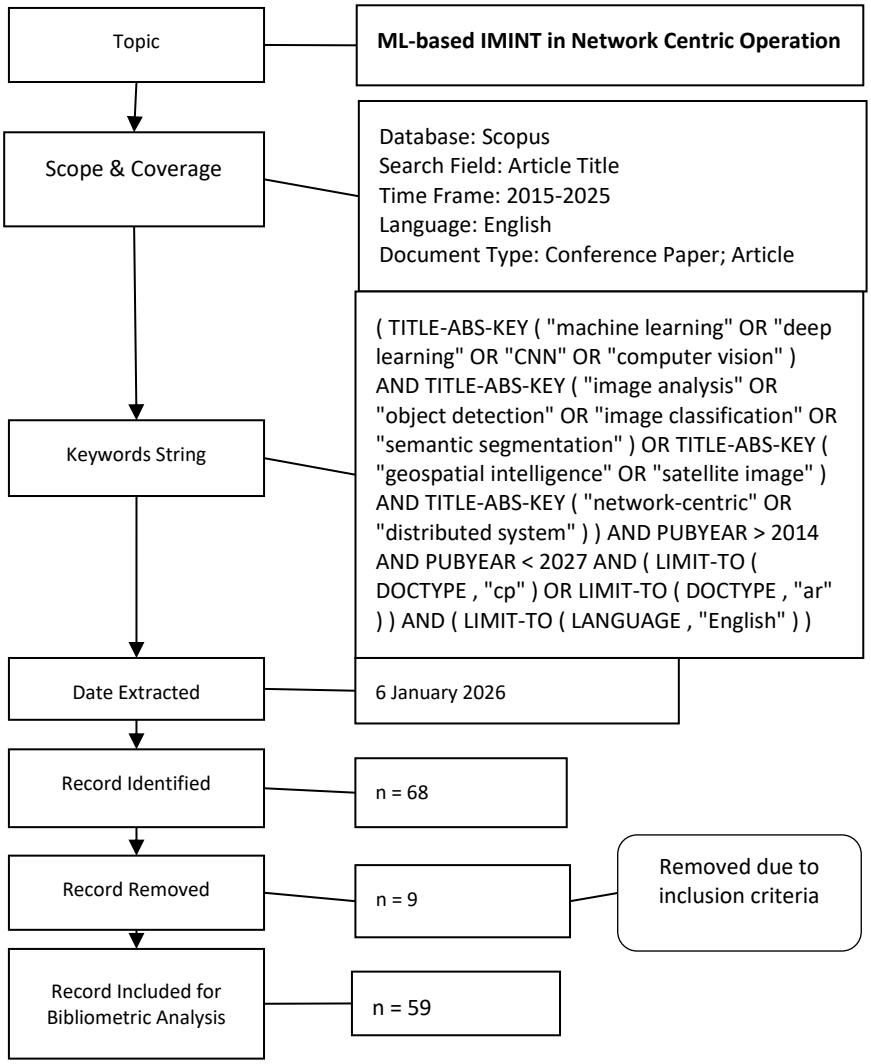


Fig.1 PRISMA Diagram

A two-pronged analytical approach was employed to identify research trend patterns and insights, ensuring a comprehensive understanding of the research landscape. The metadata (titles, abstracts, and author keywords) of the 59 selected publications were imported into VOS viewer software. A co-occurrence analysis of author keywords was performed with a minimum occurrence threshold of five terms. This threshold was selected to ensure the identification of established thematic patterns while excluding peculiar phrases that do not represent broader research directions. This generated a network visualization map that reveals the dominant thematic clusters and their interconnections within the field of distributed image analysis. The

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overlay visualization feature was further utilized to trace the temporal evolution of research focus from 2015 to 2026, identifying emerging trends.

To enhance the insights derived from the temporal co-occurrence keyword network, a comprehensive thematic synthesis was conducted on the selected publications. This process included analyzing the literature to pinpoint recurring architectural styles, fundamental algorithmic strategies, and frequently mentioned implementation obstacles. The coding framework was specifically shaped by the operational limitations pertinent to Indonesia's IMINT situation, such as intermittent connectivity, decentralized data sources, and constrained edge resources.

RESULTS AND DISCUSSION

The temporal pattern identified in the co-occurrence analysis presented in Fig. 2 below demonstrates the evolution of research, starting with the foundational stage, where the focus is on establishing robust distributed systems, network security, and basic CNN architectures. This is followed by a convergence phase, where these infrastructures are integrated with specific domains like remote sensing to perform core tasks such as object detection. Finally, the field culminates in an optimization stage, characterized by distributed deep learning and computer vision. These advanced capabilities prioritize high-level efficiency through techniques like gradient compression and lightweight modeling, which are essential for operating within resource-constrained environments.

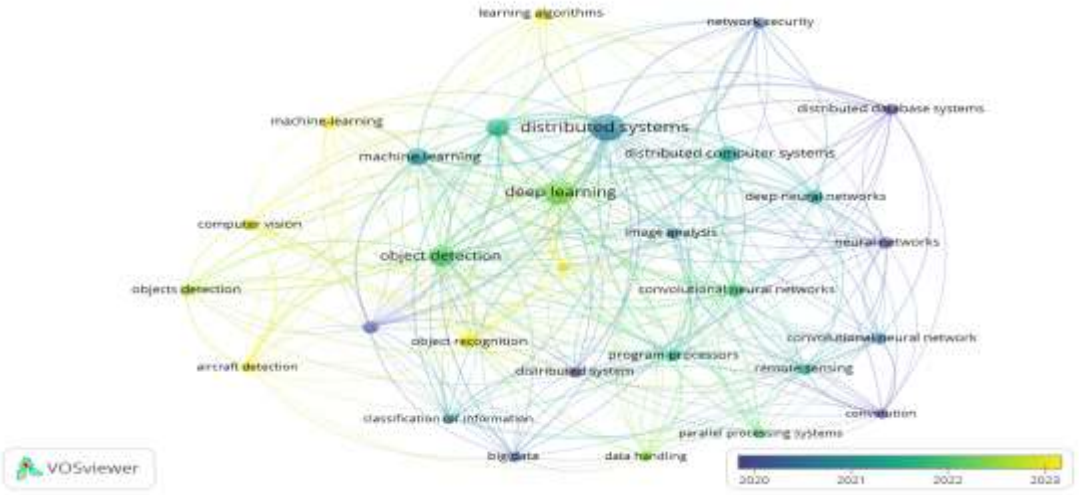


Fig.2 Temporal Map of Keywords Analyzed

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Temporal Trend: Transitioning from Infrastructure to Smart Analytical Functions

The purple nodes signify the beginning stage of a research trend that examines the essential algorithms and infrastructure necessary for their advancement. Core concepts such as distributed systems, network security, and convolutional neural networks (CNN) represent the fundamental groundwork being established alongside. Initial studies concentrated on (a) distributed computing frameworks designed to manage substantial workloads, (b) security protocols to safeguard the systems and their information, and (c) the creation of the foundational algorithm (CNN) functioning as an image processing tool. For instance, Zhang et al. (2017) assesses various distributed computing platforms, while Gomez et al. (2019) investigates encryption methods to secure CNN models. This suggests that building contemporary IMINT systems demands a concurrent foundational investment in reliable and secure distributed computing infrastructure as well as proficiency in essential algorithms.

The appearance of keywords in the blue-green nodes such as image analysis, object detection, and remote sensing indicates the convergence phase. Foundational infrastructure and algorithms (distributed systems + CNN) are combined and employed to address specific image analysis tasks within particular fields like remote sensing. Object detection serves as the primary application task that connects these elements. Binquan & Xiaohui (2019) focusing on distributed CNN for classifying targets in satellite images and Balti et al. (2019) exploring distributed systems for object detection in satellite imagery exemplify this phase perfectly. This stage could serves as a model for establishing its initial operational capabilities. The emphasis should be on integration initiatives that utilize distributed architectures and CNN for conducting object detection on remote sensing data, which is immediately beneficial for regional monitoring.

Highlighted in bright yellow nodes, keywords like computer vision, distributed deep learning, and object recognition indicate the forefront of current research. The inclusion of computer vision as the final node signifies a more intricate layer of functionalities that have transcended basic image analysis and object detection, built upon converged systems. Object recognition serves as an illustration of a capability within this domain. This stage is marked by high-level optimization (distributed deep learning) aimed at efficiently implementing these advanced functionalities. Xie et al. (2025) research on gradient compression for distributed deep learning at the edge, along with Gandor & Nalepa (2022) addressing image compression trade-offs for vision models, represents efforts to resolve efficiency challenges. This stage presents two key aspects: (1) An aspiration for advanced functionalities (computer vision, object recognition) that development can aim toward; (2) Essential optimization techniques that are crucial for

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adaptation in Indonesia. These techniques facilitate the realization of these advanced functionalities in the final stage while navigating the infrastructure limitations that pose significant challenges (Adityayuda et al., 2024).

Potential Technology Adaptation in Indonesian Network-Centric IMINT

To systematically identify the most suitable technological solutions for operational challenges inherent to IMINT development, this study synthesizes and categorizes key research findings into a curated reference catalogue, presented in Table 1. The selection of references for each category reflects a focused evaluation based on three criteria: the direct relevance of their technological contributions to overcoming specific Indonesian constraints (such as limited bandwidth and fragmented data), the conceptual maturity and proven efficacy of the proposed techniques, and the practical feasibility of their implementation within Indonesia's distinctive operational landscape characterized by diverse geography, and heterogeneous infrastructure

Table 1. Key Technologies for Network-Centric IMINT Adaptation

Solution Categories	Key Technologies	Operational Impact	Reference
Processing Architecture	Cloud-Edge Computing Hierarchy, Resilient Dataflow, Fault Tolerant Model	Ensuring continued detection at remote locations when the connection is unstable.	Ntousis et al. (2025), Tu et al. (2021), Cheng et al. (2018), Boutellier et al. (2025)
Distributed Collaboration & Security	Federated Learning (FL), Privacy-Preserving AI (DP, HE), GANs for Data Normalization	Inter-agency intelligence collaboration that does not result in sensitive data leaks	Gomez et al. (2019), Liu et al. (2020), Shen et al. (2023), Yang & Guo (2024)
Resource & Communication Optimization	Data Compression & Gradients, Lightweight Models, In-Network Computing	High bandwidth efficiency for sensor data transmission at the border region	Xie et al. (2025), Gandor & Nalepa (2022), Siddique et al. (2021), Song et al. (2021), Seo et

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			al. (2023), Han et al. (2021)
Scalable Real-Time Inference and Analysis	Stream Processing, Real-Time Multi Object Tracking Pipeline, Multi-Sensor Analysis	Fast acceleration of situational awareness from UAV/Satellite.	Karpiuk & Klym (2024), Do et al. (2024), Haq et al. (2025), Qiu et al. (2025)

Table 1 illustrates essential technologies from strategic research that should be integrated into the development of Indonesian IMINT systems. Within the context of Processing Architecture, the split computing approach that allocates the inference workload between the edge and the cloud (Cheng et al., 2018; Ntousis et al., 2025) as well as the fault-tolerant dataflow computing framework provide vital operational foundations (Boutellier et al., 2025). This architecture supports real-time task execution in remote areas with limited infrastructure, while ensuring system availability despite potential node failures or fluctuations in connectivity, which can be beneficial in difficult geographic areas.

To bridge the gaps caused by data fragmentation and institutional information sovereignty, Distributed Data Collaboration & Security technology serves as a crucial solution. Federated Learning, augmented with adaptive differential privacy techniques as stated in Liu et al. (2020) and fully homomorphic encryption technique in Gomez et al. (2019), facilitates collaborative model training without requiring the centralization of sensitive datasets. Innovations like employing Generative Adversarial Networks (GANs) to standardize data variability from various sources in Shen et al. (2023) and utilizing graph-based FL algorithms for non-IID data in satellite constellations effectively address data heterogeneity while ensuring security and privacy (Yang & Guo, 2024).

Effective operation of the system within the limitations of national infrastructure relies on resource optimization and communication factors as essential technical requirements. Advanced compression methods from Gandor & Nalepa (2022) applied both at the data (image) level and during distributed training gradients, greatly alleviate the bandwidth load, which frequently acts as a bottleneck (Song et al., 2021; Xie et al., 2025). Additionally, implementing in-network computing strategies and utilizing a lightweight microservices architecture shifts the computational load nearer to the data source, resulting in reduced latency, lower power

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consumption, and diminished reliance on high-capacity hardware (Seo et al., 2023; Siddique et al., 2021).

Ultimately, the ability to perform Scalable Real-Time Inference & Analytics is essential for obtaining actionable insights. Stream processing frameworks based on publish-subscribe models, like Apache Kafka Karpiuk & Klym (2024), along with distributed Multi-Object Tracking (MOT) systems that combine deep learning with big data solutions as studied by Do et al. (2024), enable near-real-time integration, processing, and analysis of data streams collected from multiple sensors (UAVs, satellites, CCTV). These capabilities, further enhanced by spatial-temporal analytics and hybrid cloud-edge inference methods, are crucial for creating dynamic, precise, and responsive situational awareness that aids timely operational decision-making (Haq et al., 2025; Qiu et al., 2025).

Aligning Trends with Flexibility: A Strategic Framework

Temporal analysis indicates a significant evolution in algorithms: transitioning from a large-scale parallel computing model that managed batch processing to a more flexible distributed architecture geared towards stream processing and low-latency inference. This change corresponds with the shift in IMINT needs from post-mission evaluations to real-time actionable intelligence. The adaptation catalogue subsequently translates this progression into technology components that can be pragmatically combined.

The interdependent connection is evident. Techniques such as gradient compression and split computing, created to alleviate bottlenecks in extensive deep learning systems, are essential enablers for Indonesia (Song et al., 2021; Tu et al., 2021; Xie et al., 2025). These technologies facilitate the execution of intricate models (computer vision) on constrained edge infrastructure, effectively allowing a bypass of the stage requiring substantial high-end infrastructure investment. Likewise, the rise of FL with privacy features is not merely a security approach; it represents a paradigm shift in algorithms that turns the limitations of data fragmentation into collaborative advantages (Liu et al., 2020; Shen et al., 2023). Rather than concentrating data, FL algorithms distribute the learning process itself, which is intrinsically more robust and well-suited for decentralized organizational frameworks.

Therefore, the essential understanding is that adapting technology for Indonesian IMINT is less about embracing cutting-edge research outputs and more about utilizing fundamental algorithmic techniques stemming from each stage of research evolution to create a system tailored to specific constraints. The most strategic plan is to establish split computing and

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compression as the core for efficiency, position FL as the foundation for data collaboration, and develop real-time analytical capabilities upon that base, thus creating a network-centric system that is naturally resilient, resource-efficient, and capable of organic development.

CONCLUSION

This study presents a systematic method for adapting global technological progress in distributed image analysis to improve Indonesia's network-centric IMINT capabilities. Temporal analysis trends effectively reveals evolutionary trends, transitioning from foundational infrastructure to domain integration and ultimately to advanced optimization, serving as a conceptual framework for the continuous enhancement of analytical skills.

The novelty of this research lies in the development of a catalog of technology adaptations (Table 1) that links high-level algorithmic principles (such as split computing and federated learning) with solutions to the constraints of limited national infrastructure and fragmented data. The core idea of the proposed strategy is not to completely replicate advanced systems, but rather to deliberately engineer key algorithmic principles. By combining these principles, Indonesia can transform traditional barriers into drivers of innovation, creating a resilient, adaptive, and self-sufficient IMINT ecosystem without relying on expensive, large-scale infrastructure procurement.

FUTURE DIRECTIONS

This research has a number of limitations. The analysis has not been validated through quantitative methods such as simulations or proof-of-concept assessments to confirm the effectiveness of the proposed technology integration within Indonesian infrastructure conditions. Additionally, the study mainly concentrates on technical aspects, while essential supportive elements like data policy, standardization, and workforce preparedness have not been thoroughly examined.

For future research, two key directions can be pursued. First, it is essential to conduct technical validation through simulation modelling or small-scale pilot initiatives to evaluate the real performance of split computing architectures, Federated Learning, and data compression in environments with limited bandwidth. Second, the research should be broadened to include system governance aspects by developing a policy framework for data collaboration, cybersecurity, and a collaborative operating model to facilitate the deployment of these technologies within Indonesia's multi-agency intelligence ecosystem.

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REFERENCES

Adityayuda, A., Supriyadi, A. A., & Arief, S. (2024). Development of a Remote Sensing System for Real-Time Detection of Military Threats. 2024 IEEE Asia-Pacific Conference on Geoscience, Electronics and Remote Sensing Technology (AGERS), 257–268. https://doi.org/10.1109/AGERS65212.2024.10932929

Atre, M., Jha, B., & Rao, A. (2021). Distributed Deep Learning Using Volunteer Computing-Like Paradigm. 2021 IEEE International Parallel and Distributed Processing Symposium Workshops (IPDPSW), 933–942. https://doi.org/10.1109/IPDPSW52791.2021.00144

Balti, H., Mellouli, N., Chebbi, I., Farah, I., & Lamolle, M. (2019). Deep Semantic Feature Detection from Multispectral Satellite Images. Proceedings of the 11th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management, 458–466. https://doi.org/10.5220/0008350004580466

Binquan, L., & Xiaohui, H. (2019). Effective distributed convolutional neural network architecture for remote sensing images target classification with a pre-training approach. Journal of Systems Engineering and Electronics, 30(2), 238–244. https://doi.org/10.21629/JSEE.2019.02.02

Boutellier, J., Tan, B., Nurmi, J., & Bhattacharyya, S. S. (2025). Edge-PRUNE: A Dataflow-Based Framework for Distributed Signal Processing and Machine Learning. IEEE Transactions on Signal Processing, 73, 3302–3315. https://doi.org/10.1109/TSP.2025.3598453

Chen, J., & Ran, X. (2019). Deep Learning With Edge Computing: A Review. Proceedings of the IEEE, 107(8), 1655–1674. https://doi.org/10.1109/JPROC.2019.2921977

Chen, X., Li, W., Hsu, C.-Y., Arundel, S. T., & Higman, B. (2025). Harnessing Geospatial Artificial Intelligence and Deep Learning for Landslide Inventory Mapping: Advances, Challenges, and Emerging Directions. Remote Sensing, 17(11), 1856. https://doi.org/10.3390/rs17111856

Cheng, M.-H., Sun, Q., & Tu, C.-H. (2018). An Adaptive Computation Framework of Distributed Deep Learning Models for Internet-of-Things Applications. 2018 IEEE 24th International Conference on Embedded and Real-Time Computing Systems and Applications (RTCSA), 85–91. https://doi.org/10.1109/RTCSA.2018.00019

Do, N.-T., Nguyen, N. N.-Y., Nguyen, D.-P., & Do, T.-H. (2024). RAMOTS: A Real-Time System for Aerial Multi-Object Tracking Based on Deep Learning and Big Data Technology. 2024 16th International Conference on Knowledge and System Engineering (KSE), 01–06. https://doi.org/10.1109/KSE63888.2024.11063545

Gandor, T., & Nalepa, J. (2022). First Gradually, Then Suddenly: Understanding the Impact of Image Compression on Object Detection Using Deep Learning. Sensors, 22(3), 1104. https://doi.org/10.3390/s22031104

Gomes, D., Hasan, M., & Philip, S. R. (2025). Enhancing Capabilities and Security Features of Drone Networks Through Machine Learning: A Comprehensive Overview (pp. 81–105).

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https://doi.org/10.1007/978-3-031-80961-3_5
Gomez, L., Wilhelm, M., Márquez, J., & Duverger, P. (2019). Security for Distributed Deep Neural Networks Towards Data Confidentiality & Intellectual Property Protection. ArXiv, abs/1907.04246. https://api.semanticscholar.org/CorpusID:195847875
Han, R., Si, M., Demmel, J., & You, Y. (2021). Dynamic scaling for low-precision learning. Proceedings of the 26th ACM SIGPLAN Symposium on Principles and Practice of Parallel Programming, 480–482. https://doi.org/10.1145/3437801.3441624
Haq, B., Kasi, B., Kasi, M., & Haider, S. K. (2025). Spatial-Temporal Deforestation Forecasting via Remote Sensing and Artificial Intelligence Driven Sensor Networks. Mobile Networks and Applications, 30(3–4), 414–421. https://doi.org/10.1007/s11036-025-02462-9
He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 770–778. https://doi.org/10.1109/CVPR.2016.90
Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., & Adam, H. (2017). MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. ArXiv, abs/1704.04861. https://api.semanticscholar.org/CorpusID:12670695
Karpiuk, N., & Klym, H. (2024). Streamlined Near Real-Time Image Processing with Apache Kafka. 2024 14th International Conference on Dependable Systems, Services and Technologies (DESSERT), 1–5. https://doi.org/10.1109/DESSERT65323.2024.11122032
Liu, X., Dong, X., Jia, N., & Zhao, W. (2024). Federated Learning-Oriented Edge Computing Framework for the IIoT. Sensors, 24(13), 4182. https://doi.org/10.3390/s24134182
Liu, X., Li, H., Xu, G., Lu, R., & He, M. (2020). Adaptive privacy-preserving federated learning. Peer-to-Peer Networking and Applications, 13(6), 2356–2366. https://doi.org/10.1007/s12083-019-00869-2
Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2010). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. International Journal of Surgery, 8(5), 336–341. https://doi.org/10.1016/j.ijsu.2010.02.007
Ntousis, O., Makris, E., Tsanakas, P., & Pavlatos, C. (2025). A Dual-Stage Processing Architecture for Unmanned Aerial Vehicle Object Detection and Tracking Using Lightweight Onboard and Ground Server Computations. Technologies, 13(1), 35. https://doi.org/10.3390/technologies13010035
Qiu, J., Yin, F., Wang, B., & Liang, B. (2025). Edge-Cloud Cooperative Inference for Semantic Segmentation Models (pp. 1–13). https://doi.org/10.1007/978-981-96-1698-5_1
Seo, J., Jang, S., Cha, J., Choi, H., Kim, D., & Kim, S. (2023). MDED-Framework: A Distributed Microservice Deep-Learning Framework for Object Detection in Edge Computing. Sensors, 23(10), 4712. https://doi.org/10.3390/s23104712
Shen, Y., Sowmya, A., Luo, Y., Liang, X., Shen, D., & Ke, J. (2023). A Federated Learning System for Histopathology Image Analysis With an Orchestral Stain-Normalization GAN. IEEE

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Transactions on Medical Imaging, 42(7), 1969–1981. https://doi.org/10.1109/TMI.2022.3221724

Siddique, H., Neves, M., Kuzniar, C., & Haque, I. (2021). Towards Network-accelerated ML-based Distributed Computer Vision Systems. 2021 IEEE 27th International Conference on Parallel and Distributed Systems (ICPADS), 122–129. https://doi.org/10.1109/ICPADS53394.2021.00021

Song, L., Zhao, K., Pan, P., Liu, Y., Zhang, Y., Xu, Y., & Jin, R. (2021). Communication Efficient SGD via Gradient Sampling with Bayes Prior. 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 12060–12069. https://doi.org/10.1109/CVPR46437.2021.01189

Tu, C.-H., Sun, Q., & Cheng, M.-H. (2021). On designing the adaptive computation framework of distributed deep learning models for Internet-of-Things applications. The Journal of Supercomputing, 77(11), 13191–13223. https://doi.org/10.1007/s11227-021-03795-4

Xie, W., Ma, J., Lu, T., Li, Y., Lei, J., Fang, L., & Du, Q. (2025). Distributed Deep Learning With Gradient Compression for Big Remote Sensing Image Interpretation. IEEE Transactions on Neural Networks and Learning Systems, 36(8), 14328–14342. https://doi.org/10.1109/TNNLS.2024.3517535

Yang, A., & Guo, C. (2024). GraphFed-Swarms: Large-Scale Satellite Constellations Space-Based Distributed Computing with Graph Information Aggregation Federated Learning. IAF Space Operations Symposium, 887–896. https://doi.org/10.52202/078367-0095

Zhang, K., Alqahtani, S., & Demirbas, M. (2017). A Comparison of Distributed Machine Learning Platforms. 2017 26th International Conference on Computer Communication and Networks (ICCCN), 1–9. https://doi.org/10.1109/ICCCN.2017.8038464

Zwane, S., Tarwireyi, P., & Adigun, M. (2018). Performance Analysis of Machine Learning Classifiers for Intrusion Detection. 2018 International Conference on Intelligent and Innovative Computing Applications (ICONIC), 1–5. https://doi.org/10.1109/ICONIC.2018.8601203

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