REVIEW ARTICLE

Computer Vision-Powered 6G Networks: Technologies, Applications, and Challenges

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Abstract

Aiming to move from conventional throughput-centric paradigms to intelligent, context-aware systems able of perception and autonomous decision-making, sixth-generation (6G) wireless networks is seeking. Driven by recent developments in deep learning and edge artificial intelligence, computer vision (CV) proves to be a key enabler for such perceptive 6G systems. This paper offers a thorough overview bringing together the scattered terrain of CV-enabled 6G technologies. It benchmarks current models against major 6G performance criteria, evaluates architectural paradigms including federated and split learning, and presents a disciplined taxonomy of use cases. This study also notes the possibility of incorporating new technologies with CV to make it more effective, such as fluid antenna system (FAS) and fluid antenna multiple access (FAMA). The study shows that CV integration improves fundamental 6G capabilities like beamforming, mobility prediction, localisation, semantic communication, and immersive control. It also reveals limits in real-time inference under URLLC constraints, data scarcity, and energy economy, though. This work presents a unified basis for advancing CV-native 6G networks by spotting open challenges and suggesting a roadmap including generative perception, collaborative intelligence, and green vision computing.

Keywords: computer vision, 6G wireless networks, FAS, edge intelligence, semantic communication, vision-aided 6G applications.

Submitted: 24 June 2025
Accepted: 11 July 2025
Published: 28 July 2025

Vol. 1, **No.** 1, 2025.
10.62762/TMWI.2025.159776

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1 Introduction

Sixth-generation (6G) wireless networks represent a paradigm change from simple high-throughput connectivity towards highly integrated, intelligent, and perceptive systems. Unlike 5G, which concentrated on improvements in latency, data rates, and spectral efficiency, 6G aims to embed cognition, context-awareness, and semantic understanding into the network itself. The convergence of artificial intelligence (AI) [1–3], edge computing, and multi-modal sensing drives this metamorphosis mostly. Among the several fields covered under artificial intelligence, computer vision (CV) has become a particularly effective enabler of 6G capabilities. CV is expected to be central in realising self-adaptive, autonomous, and goal-driven communication environments since it can extract rich spatial and semantic information from the physical

Citation
Oukebdane, M. A., & Shah, A. F. M. S. (2025). Computer Vision-Powered 6G Networks: Technologies, Applications, and Challenges. *ICCK Transactions on Mobile and Wireless Intelligence*, 1(1), 19–31.

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world [4, 5].

Not only is it advantageous but also required to include CV into 6G networks. Wireless signals become quite sensitive to environmental conditions including blockage and fast fading as communication moves into the terahertz and millimeter-wave domains [37]. Under such conditions, vision sensors installed at base stations, drones, or edge nodes can continuously monitor the physical scene and allow predictive and context-aware changes to beamforming, resource allocation, and handoff decisions [11, 16, 18]. CV helps predict user movement, obstacles, and task states in real time in ultra-reliable low-latency communication (URLLC) scenarios, such remote surgery or industrial automation, so enabling networks to take proactive rather than merely reacting to channel variations [19, 20].

Still another crucial incentive is the growing emphasis on edge intelligence. As connected devices including wearables, drones, and cars become more plentiful, centralised inference becomes both useless and harmful in terms of privacy. Emerging techniques including Federated Learning (FL) and Split Learning (SL) present interesting solutions by letting model training and inference occur near the data source without distributing sensitive visual content. This distributed approach is particularly useful in sectors including healthcare, smart cities, and critical infrastructure where latency and privacy are paramount [12].

Moreover, exact visual perception is essential for 6G's goal to support completely immersive services including the metaverse and digital twins [21]. CV serves as the sensory layer in many applications that helps to match physical objects with their virtual equivalents. Essential for immersive and interactive experiences, real-time vision feedback allows precise avatar behaviour, gesture recognition, and scene reconstruction. Together with AI-powered digital twins, CV can also support remote monitoring of industrial systems, cyber-physical coordination, and predictive maintenance [4, 22].

Fluid Antenna Systems (FAS) are reconfigurable antenna structures often fluidic, dielectric, or conductive that dynamically adjust their shape or position to optimize radio-frequency characteristics, enabling enhanced signal diversity and interference mitigation. Fluid Antenna Multiple Access (FAMA) builds on this by allowing users to reposition their antennas to maximize signal-to-interference ratio (SIR), reducing the need for complex signal processing or channel state information, which is especially valuable in dense 6G environments. The main goal of 6G is to combine sensing and communication where FAS can help with that by making integrated sensing and communication (ISAC) possible. This will make it possible for vision-based applications like self-driving cars, smart surveillance, and immersive AR/VR experiences to know what's going on in the environment and where things are in real time [13–15].

A pillar of 6G, semantic communication is another area where CV is absolutely essential. Conventional networks mostly aim to precisely transmit raw data. Semantic networks, on the other hand, seek to send just pertinent, meaningful information. Here, by extracting high-level semantic cues such as intent, posture, and gestures from visual data, CV becomes rather important. After then, these cues can be more effectively encoded and transmitted, so drastically lowering bandwidth requirements and improving interpretability [10]. New research has shown that machine learning (ML) is the most important part of 6G's foundations. This includes not only signal processing and edge optimisation, but also smart and privacy-aware architectures [40]. This convergence makes for a great environment for CV to be a top-tier way to do things in the larger ML-driven network ecosystem.

Table 1 shows a combined review of current high-impact survey papers on CV, artificial intelligence, and 6G communication. Although many works have examined specific elements such beamforming [7], mobility management [8, 51], GPS localisation [6], or federated learning [12, 12], they remain siloed in scope. Most current studies either completely ignore CV or fail to fully contextualise its potential in tandem with other 6G enablers including digital twins [4], semantic communication, integrated sensing and communication (ISAC). Just a few address cross-technology convergence or dataset availability. By contrast, this survey presents a consistent and all-encompassing treatment of the CV–6G nexus. Incorporating system-level concerns including privacy, URLLC compliance, and digital twin-driven feedback, it spans many fields: beamforming, handover prediction, semantic processing, and edge AI [4, 10, 12]. This all-encompassing strategy not only fills in open research gaps but also specifies a fresh path for including perception-driven intelligence into the 6G wireless fabric. We present a thorough taxonomy of

Table 1. Comparative summary of recent survey papers.

Paper	CV for Beamforming	CV for Handoff	FL/Edge-AI	Digital Twin	ISAC/URLLC	Semantic Comm	Dataset Review	FAS/FAMA
[7]	✓	✓	x	x	✓	x	✓	x
[8]	✓	✓	x	x	✓	x	x	x
[6]	x	x	x	x	x	x	✓	x
[9]	x	x	x	x	✓	x	x	x
[10]	x	x	✓	✓	✓	✓	x	x
[11]	x	x	x	✓	✓	x	x	x
[44]	x	x	✓	✓	✓	x	✓	x
[12]	x	x	✓	x	x	x	x	x
[13]	x	x	x	x	x	x	x	✓
Our Work	✓	✓	✓	✓	✓	✓	✓	✓

the main uses of CV in 6G environments and underline their importance in improving several tiers of the communication stack in the next part.

The present research scene is scattered even with these interesting prospects. Several works separately address vision-based beamforming, mobility prediction, localisation, and traffic classification [2, 16, 17]. Some surveys address enabling technologies for 6G such as digital twins, semantic layers, and privacy-preserving artificial intelligence but treat CV either superficially or as a secondary tool [1, 4, 12]. Therefore, a thorough survey combining these developments and provides a disciplined, forward-looking perspective of CV as a first-class citizen in 6G architectures is absolutely needed.

This work provides the first complete-stack survey aimed at the integration of CV in 6G networks, so meeting that demand. It harmonises studies across architectural designs, learning paradigms, deployment techniques, and application levels. More precisely, the paper makes five main contributions:

- It suggests a fresh taxonomy based on important 6G capabilities including beam prediction, handover, localisation, traffic classification, and immersive communication that groups CV use cases.
- It offers a system-level picture of CV's interactions with other 6G enablers including semantic networking, digital twins, federated learning, and ISAC.
- It evaluates and benchmarks accessible datasets, so stressing the shortcomings in present data resources and the possibilities for simulation-based generation with digital twins.
- We highlighted CV models used in real-time communication environments trade-offs between latency, accuracy, bandwidth, and energy economy.
- This work puts FAS/FAMA-CV integrated system in the spotlight, where it explores the possibility and insights of merging them.
- We point up open research challenges and presents vision-based RIS control, generative perception, cross-device CV coordination, and sustainable vision computing as new directions.

This work is arranged restingly as follows. Section 2 presents the fundamental theoretical underpinnings and main enablers enabling CV integration in 6G networks: semantic communication, integrated sensing and communication (ISAC), digital twins, and edge learning paradigms. Section 3 systematically arranges CV-aided applications based on their function in 6G systems, so offering a complete taxonomy. Section 4 investigates the architectural frameworks needed to enable scalable and privacy-preserving CV deployments spanning the edge–cloud continuum. While Section 5 details future research directions including generative vision, RIS-assisted control, and quantum CV, for the addressed open research challenges including real-time inference, privacy risks, and explainability constraints. At last, Section 6 summarises the main findings of the survey together with a road map for including perception-driven intelligence into next-generation wireless systems.

2 State of art

By including perception, cognition, and automation into the very fabric of the network, the expected sixth-generation (6G) wireless systems seek to radically rethink communication. Rising from the constraints of 5G, 6G is expected to enable ultra-massive connectivity, near-zero latency, sub-centimeter localisation, and semantic-level information exchange, so supporting use cases including the metaverse, holographic communication, autonomous vehicles, and remote brain-computer interfacing [4, 10, 38, 39, 41].

Concurrent with this change in classical image analysis to deep learning-powered perception systems capable of real-time scene understanding, spatial awareness, and predictive modelling is CV. Fusion of CV with wireless communication technologies has become a transforming paradigm as 6G networks aim to become perceptive and native-AI infrastructues.

2.1 Development of CV towards Network Intelligence

Originally limited to surveillance and automation, CV has lately become popular in wireless systems by means of deep convolutional neural networks (CNNs), Vision Transformers (ViTs), and attention-based encoders for tasks including beam selection, blockage prediction, and mobility management [7, 23, 24]. These systems augment physical layer decisions using camera data and visual semantics, so generating new ideas including vision-aided beamforming and vision-guided proactive handoff in THz communication environments [8, 26].

Further potential to overcome GNSS restrictions in dense urban or indoor deployments is shown by pixel-level localisation methods using visual odometry and GPS fusion [6]. Furthermore opening the door for CV to be crucial in traffic steering and anomaly detection is real-time packet classification using image-based CNN encoders [28].

2.2 Essential Technologies Making Vision-Driven 6G Networks Possible

Recent work underline the fundamental contribution of deep learning architectures in enabling CV for 6G, especially through distributed intelligence frameworks such FL, split learning (SL), and edge inference [12, 43]. These paradigms enable cooperative, distributed training and inference across edge devices, UAVs, and vision sensors so addressing bandwidth, privacy, and latency bottlenecks.

Vision integration is also under investigation in concert with technologies including reconfigurable intelligent surfaces (RIS), high-altitude platform systems (HAPS), and integrated sensing and communication (ISAC [4, 19, 45, 61]. For THz bands, for example, CV systems can increase blockage awareness by combining spatial visuals with environmental dynamics, so improving beam selection accuracy.

2.3 Digital Twins and Semantic Communication

Acting as real-time digital copies of physical environments, digital twin systems have become fundamental in 6G network architecture. Continuous environmental context from CV feeds these twins supporting adaptive control, localisation, and beamforming updates [17]. Using immersive CV interfaces, metarobotics and cognitive digital twins (cogDTs) enable remote operation and instruction in manufacturing and smart industry settings [11, 48].

Semantic communication models, meantime, aim to send just "meaningful" information derived from multimodal sources. Here CV is rather important since it helps extract, compress, and transmit high-impact visual features rather than raw data [10].

2.4 Benchmarking, Datasets, and Limitations

Right now, not many datasets fit for CV applications specifically for 6G exist. Initial contributions including ViWi, VOMTC, and PixelGPS reflect handoff prediction, CV-aided beam management, and GPS denoising [6, 27]. Still, a main void remains general lack of large, realistic, and diverse datasets for tasks including RIS control, HAPS coordination, and real-time CV inference under latency/energy constraints [4]. Low generalising of CV models across geographic and environmental settings, lack of explainability, and high energy costs for real-time vision inference especially in FL/edge settings add more challenges [11, 12, 52].

3 CV-Aided Use Cases in 6G

A major enabler for reaching really intelligent, context-aware, and perceptive 6G wireless networks is CV. The natural ability of CV systems to extract rich semantic information from visual data complements conventional signal-based metrics, so enabling wireless networks to actively adapt to their environment. Several pioneering research have shown how vision can be included into wireless communication pipelines to solve restrictions in beamforming, mobility management, localisation, even network security.

Especially in millimeter-wave (mmWave) and terahertz (THz) bands where the sensitivity to line-of-sight (LoS) blockage presents major challenges, CV in 6G has one of the most fascinating applications in vision-aided beamforming and blockage prediction. From RGB or RGB-D images, vision-based systems can deduce environmental geometry and object positions that can then be used to predict ideal beam directions prior to signal degradation beginning. Thanks in great respect to the VOMTC and VOBEM datasets, deep learning models including CNNs and vision transformers that map real-time images to beam indices with great accuracy have been trained [8]. Applied in ultra-reliable low-latency communication (URLLC), these models unveil sub-10 millisecond latency and accuracy exceeding 95%. This proactive adaptation increases connectivity and helps to avoid handover delays in highly urban projects.

Likewise, the addition of CV modules has seen notable developments in proactive mobility and handover management. Conventional handover systems respond to changes in signal strength; but, with CV, networks can predict user or vehicle trajectories, classify dynamic objects (e.g., pedestrians, vehicles), and project the need for cell reselection. Vision-based mobility management systems where convolutional recurrent neural networks (e.g., ConvGRU) process sequential frames to forecast link blockages or mobility events have been presented in studies including [29–31]. By over 40% reduction in latency, preemptive handoff decisions help to improve service continuity in non-line-of-sight (NLoS) environments. Particularly in scenarios with great user mobility such vehicle networks and UAV-assisted communications, visual context from street scenes, vehicle orientation, and obstacle prediction supports dynamic radio link reassignment [32].

Another vital field where CV provides significant improvements is localisation and positioning. Significant mistakes in urban canyons or dense environments plague traditional GPS-based systems. CV can thus be combined with THz beam characteristics including angle-of-arrival (AoA) and delay spread to improve localisation estimates and so help to mitigate this. By combining RGB images with wireless beam feedback, using a neural architecture that lowered localisation error below 0.5 meters, pixel-level GPS localisation was accomplished in [6]. Furthermore, beam-based fingerprinting can be used to augment visual simultaneous localisation and mapping (SLAM), so allowing sub-meter indoor positioning critical for industrial automation and AR/VR applications in the 6G era.

Traffic classification and network security depend on CV even beyond enhancements in the physical layer. Translating packet-level data into image-like matrices allows convolutional neural networks to be highly accurately used to detect anomalies, intrusions, and denial-of- service (DoS) attacks. Low false positive rates indicate how CV-inspired models can be trained on packet visualisations to get classification accuracy almost close to 99%. These models are particularly useful when standard signature-based intrusion detection fails in encrypted or obfuscated traffic conditions. Moreover, the computational simplicity of modern CV models guarantees low latency when applied at edge servers or base stations, so preserving real-time threat reducing characteristics [42].

Furthermore advancing immersive metaverse environments and 6G-enabled smart factories is CV. By means of immersive interfaces such as VR and AR, CV allows real-time visual monitoring and control of remote robots, so enabling ubiquitous and itinerant human–robot cooperation (pi-HRC) in the metarobotics vision proposed by [11, 49]. While CV decodes gestures, spatial interactions, and user intent, such systems rely on 6G's ultra-low-latency and high-bandwidth capabilities to stream high-density visuals. Applications abound from remote learning to industrial automation and tailored healthcare. CV's impact increases even more when one includes digital twins, collective artificial intelligence, and holographic displays which provide both control and feedback loops between real-world and virtual objects [47, 59, 60].

UAV-based CV applications find traction in on-demand coverage, surveillance, and disaster recovery. CV-equipped drones can evaluate coverage gaps, find human presence, and evaluate terrain using onboard cameras run under either lightweight CNNs or YOLO variants. Using vision-driven environmental awareness in [33] drones changed their formation and ensured strong wireless coverage in real time. These drones can also interact with reconfigurable intelligent surfaces (RIS) and high-altitude platform stations (HAPS), so optimising coverage zones dependent on visual context and expected obstacles.

Table 2 offers a necessary overview of main CV-aided usage cases in 6G wireless systems. Every row focusses on a particular application domain including the type of visual input used, the applied CV techniques, the matching 6G function enabled, and the published performance measurements from current work. Important disciplines ranging from beamforming to mobility prediction, localisation, security, industrial control, and UAV-based sensing are found here. This ordered review not only shows the spectrum of CV applications in 6G but also highlights the increasing need of including perception-driven intelligence into next wireless systems.

By extending the perceptual limit of 6G networks,

Table 2. Summary of CV-Aided use cases in 6G.

Use Case	Vision Input	CV Technique	6G Function	Performance
Beamforming & Blockage Prediction	RGB, RGB-D video	CNN, ViT	Beam index prediction, LoS classification	Accuracy >95%, Latency <10ms
Proactive Mobility & Handover	RGB video sequences	ConvGRU, ResNet	Mobility prediction, link reassignment	Latency ↓ 40%
Localization & SLAM	RGB + Beam data	Neural Fusion, DNN	Sub-meter positioning, GPS refinement	0.43m RMSE, 25ms latency
Traffic Classification & Security	Packet images	CNN classifier	Anomaly/DoS detection	98.9% accuracy, Low FPR
Industrial Control & Metaverse	Live video streams	YOLOv8, ViT	Robot interaction, control in digital twins	Realtime actuation, immersive control
UAV-Based Vision Sensing	Onboard drone camera	Lightweight CNN, YOLO	Disaster mapping, coverage extension	Scene-aware pathing, realtime updates

CV helps them to see, reason, and change with their surroundings. Whether for beamforming, mobility, localisation, security, or industrial automation including CV into communication pipelines marks a paradigm change from reactive to proactive and intelligent network operation. As 6G networks develop more efficient, privacy-conscious, and closely linked with edge computing, CV models will become ever more crucial.

4 Architectures for enabling CV in 6G

Combining CV into 6G network designs calls for a rethink of the traditional wireless communication stack. Unlike past generations, 6G is made to be intrinsically AI-native, semantic-aware, and sensing-integrated, so providing a rich ground for embedding CV functions straight into communication pipelines [4, 10]. Examining layered deployments, computing paradigms, hardware/software integration, and the interaction with enabling technologies including semantic communication, federated learning, and digital twins, this section discusses the architectural paradigms that enable the smooth adoption of CV technologies in 6G systems.

4.1 Joint CV-Communication Architectural Layers

In 6G, CV is expected to be buried across several layers of the communication stack. Vision sensors including RGB, depth, infrared, and multispectral cameras continuously record the surroundings at the **perception layer**. Lightweight CNNs or vision transformers (ViTs) applied either on the device or at edge nodes [1] preprocess these data. Real-time inference, feature extraction, and local decision-making fall to the edge intelligence layer [50]. For applications including proactive beam steering and mobility management, where millisecond-level responsiveness is needed [8], this is absolutely vital. Rather than raw video streams, the **communication layer** sends semantically compressed or feature-level data, so drastically lowering the bandwidth demand [10]. At last, the **cognitive orchestration layer** uses artificial intelligence agents to coordinate among CV insights, digital twin simulations, and network optimisation modules.

Figure 1 shows a layered architecture that catches the end-to- end integration of CV inside a 6G network system. At the base, several imaging modalities including RGB, depth, and thermal cameras that serve environmental sensing comprise the perception layer. After capture, the data is sent to the edge intelligence layer, where lightweight CV models run real-time inference often improved with federated or split learning techniques. After that, semantic representations of these visual insights are encoded and sent across the communication layer, so conserving context and so lowering bandwidth. Feeding into the digital twin layer, which keeps a synchronised simulation of the physical environment, the cognitive orchestration layer uses artificial intelligence agents to interpret semantics and change network parameters. A basic design for future 6G

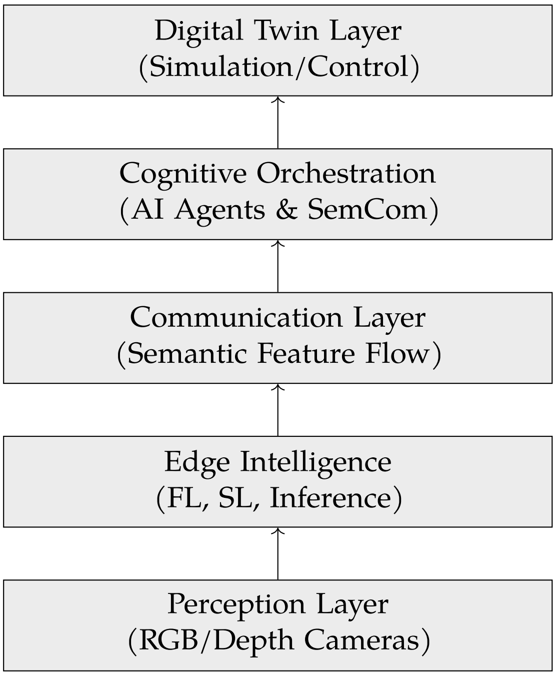

Figure 1. Multi-layered CV-communication architectural stack in 6G.

systems, this architectural layering not only supports real-time CV-driven network adaptation but also proactive decision-making.

4.2 Integrating Computer Vision with FAS/FAMA in 6G Networks

Since 6G networks is driving towards an URLLC, the well use of the spectrum is a major requirement, where CV and FAS combination can be an incredible solution for that. FAS is known by its ability to create an adaptable physical layer wich lets one antenna move between spatial ports in real time to boost the signal as discussed in those studies [13–15, 53–58]. Therefore, we can use CV as helper for a more smooth operating FAS where it will take the advatage of it to help find things in the way, it guess where the user will go, or figure out where they might be, in order to make the system able to place the antennas ahead of time in the most probable place where the user will be thus avoid and stops the link from getting worse. FAMA builds on FAS to let these dynamic antennas serve more than one user by taking advantage of interference fading characteristics [13]. This makes the hardware much simpler while also increasing the chances of an outage and the multiplexing gain.

4.3 Edge/Fog-Based Offloading of Vision Tasks

Vision tasks are offloaded to edge or fog nodes to help end devices overcome their limited resources. Real-time applications including dynamic handoff prediction and UAV path correction [4, 25] are made possible by these nodes hosting models tuned for latency-sensitive inference. Techniques for model partitioning such quantization-aware training and split learning (SL) help distribute computational loads over the edge-cloud continuum [11, 12]. This allows a scalable and flexible deployment of CV systems without endangering user privacy or system performance [12].

4.4 Distributed CV via Federated and Split Learning

FL has become a main enabler for 6G [12] vision systems preserving privacy. Aggregated at edge servers, CV models trained locally on user or sensor devices avoid the need to broadcast raw data. Applications involving sensitive images or personalised vision models (e.g., smart healthcare, AR/VR in metarobotics) [11] especially depend on this. By letting deep models be split across servers and devices, split learning balances inference latency and privacy in complementing FL.

Table 3 shows for a comparison of three well-known learning paradigms centralised, federated, and split learning for 6G network deployment of CV models. Every paradigm is ranked covering important performance criteria including domain fitfulness, inference latency, data privacy, and training overhead. Although centralised learning is resource-intensive and privacy-limited, for applications like packet classification needing mass data access it is still appropriate. Perfect for applications in smart cities and healthcare where sensitive data is abundant, federated learning keeps data local and improves privacy. Split learning offers the lowest latency and best privacy characteristics by distributing model segments over the edge and cloud; these are important in environments including UAV navigation or immersive AR/VR systems. Emphasising the need of context-aware architecture design in vision-activated 6G systems, this comparison reveals that none of any technique is always best.

4.5 Semantic Communications and Knowledge-Aware CV Pipelines

Semantic communication (SemCom) lets one send just task-relevant features instead of whole data frames. High-level semantics (e.g., detected object class, mobility intent, or scene label) extracted by CV modules is compiled into compact messages [10]. These signals not only help to maximise channel use

Table 3. Comparison of learning paradigms for vision in 6G.

Learning Type	Privacy	Latency	Overhead	Use Cases
Centralized	Low	Moderate	High	Beamforming, Classification
Federated	High	Low	Medium	Smart cities, HAPS, Healthcare
Split	Very High	Very Low	Low	UAVs, AR/VR, Metaverse

but also let AI agents in the orchestrating level make contextual decisions. Visual data across heterogeneous networks is interpreted using knowledge graphs and ontologies so improving interoperability in multi-agent systems [46].

4.6 Vision Integration in Digital Twin and Metarobotic Systems

In 6G digital twins (DTs) are live, synchronised digital copies of the physical world. Feeding these DTs real-time environmental perceptions [4] depends critically on CV. CV pipelines provide the sensory interface between users and remote environments in industrial and metarobotic settings, so enabling teleoperation, remote maintenance, and holographic collaboration [11]. For semantic rendering and closed-loop actuation, these pipelines have to be closely linked with DT models.

Enabling architectures for CV in 6G are defined in general by deep vertical integration from perception to orchestration layers, horizontally distributed intelligence across edge-cloud infrastructues, and semantic-aware communication pipelines. Together, these architectural innovations open the path for smart, strong, low-latency visual intelligence in 6G systems.

5 Challenges and Future Research Directions

By including CV into the fabric of 6G wireless networks, beamforming, mobility, localisation, and immersive services acquire hitherto unusual capability. But this convergence also raises several cross-domain issues that are mostly unresolved in current literature.

5.1 Technical and Operational Challenges

Real-time perception and inference under ultra-reliable low-latency communication (URLLC) constraints presents one of the most urgent problems. While 6G targets sub-millisecond latency and 99.99999% reliability, current CV models—especially those based on deep neural networks such Vision Transformers—need considerable computational overhead and often fail when implemented on edge nodes with limited resources [4, 33]. An open design challenge remains balancing strict latency budgets with high-resolution visual input processing [12, 34–36].

Furthermore lacking standard interfaces and architectural cohesiveness is interoperability between CV models and multi-modal sensing modalities including RF, LiDAR, and semantic communication agents [10]. While coping with the domain shift caused by various environmental and device conditions, vision systems in 6G must smoothly co-function with integrated sensing and communication (ISAC) layers.

Edge deployment creates a different set of trade-offs. Vision-activated inference pipelines have to be maximised for power economy without sacrificing prediction or detection accuracy. However, present solutions sometimes depend on cloud offloading, which compromises privacy guarantees and latency. Moreover, although promising, the federated and split learning paradigms suffer from data heterogeneity, lack of personalising for vision-centric tasks, and communication bottleneck [12].

Particularly with the increasing CV in consumer and industrial environments, privacy, explainability, and trustworthiness are becoming issues. Distributed CV applications in smart cities, surveillance, and healthcare run hazards of information leaking, model inversion, and inadvertent bias [10]. Further complicating the deployment of CV in mission-critical situations including drone navigation or industrial automation is the absence of explainable visual intelligence.

Lack of comprehensive, labelled datasets particular to 6G-CV activities is another major bottleneck. Particularly under extreme mobility or adversarial interference [23], vision-for-wireless datasets including VOMTC or ViWi have limited diversity and resolution. This scarcity prevents generalisation over use cases, benchmarking, and transfer learning.

5.2 Research Roadmap and Emerging Trends

Several future directions show great promise in filling in the above mentioned challenges. First, generative vision models including conditional GANs and diffusion models can be used to synthesis realistic training data for different environments, so supporting digital twin-based simulations for vision-enabled network control [35]. For beam prediction, obstacle recognition, and user localisation, such methods can empower zero-shot or few-shot learning strategies.

Second, especially in settings with high device density and low latency budgets [4], quantum CV is expected to open fresh frontiers in encoding, pattern matching, and low-complexity visual inference. Classical neural models implemented in RIS-enhanced environments can be complemented by quantum-assisted visual feature extraction and classification.

Third, especially in mission-critical sectors including Industry 4.0 and remote healthcare, the use of federated digital twins enhanced by real-time visual feedback can enable proactive network orchestration. By means of visual data from UAVs, cameras, or robots, digital twins can be continuously updated, so enabling context-aware communication parameter configutation.

Furthermore opening the path for vision-driven actuation is the emergence of Reconfigurable Intelligent Surfaces (RIS). RIS panels can dynamically change phase shifts in response to sensed environmental changes by coupling object detection outputs with beam steering logic [10]. This requires light weight CV agents working under strict timing restrictions.

Furthermore acquiring popularity are multi-agent CV systems and swarm intelligence. Collaborative CV allows agents to share processed vision features for coordinated sensing, mapping, and trajectory planning so benefiting imagined 6G networks with dense UAV constellations or autonomous vehicles.

Sustainability still understudied but yet vital aspect. Battery-limited edge devices depend critically on green CV designs—optimized for energy-aware training and inference. Expected to define the next phase of edge-compatible CV deployment are innovations in pruning, quantisation, and sparsity-based modelling [25].

In the framework of CV integration inside 6G networks, Table 4 offers a structured synthesis of the central cross-domain challenges and their related research directions. Every difficulty, from real-time inference under URLLC restrictions to the lack of explainability in CV decisions, is in line with practical and developing research paths anchored in recent

Table 4. Summary of core challenges and research directions.

Challenge	Research Direction
Real-time CV under URLLC	Green models and on-device inference optimization
Multi-modal interoperability	CV-RF-LiDAR fusion protocols and standard APIs
Data scarcity and annotation cost	Synthetic dataset generation via generative models
Privacy and ethics in vision AI	Federated learning with differential privacy
Explainability of CV decisions	Post-hoc and embedded XAI for CV pipelines
Latency-power-accuracy tradeoffs	Adaptive inference pipelines with edge/cloud orchestration

literature. This mapping not only shows the present technological bottlenecks but also points up interesting directions including synthetic dataset generation using generative models, federated learning with privacy guarantees, and energy-aware CV inference systems. Consolidating these aspects helps to be a fundamental reference for next studies and system design in vision-aided 6G environments.

To sum up, including CV into 6G wireless networks is both exciting and quite difficult. By means of multidisciplinary approaches—combining wireless communication, machine learning, quantum computing, and ethics—addressing the above challenges will open the road towards natively intelligent 6G ecosystems.

6 Conclusion

Viewed through an interdisciplinary perspective, we investigated how CV goes beyond conventional roles to become a native enabler of proactive, intelligent, and perceptually conscious networks. We unified the varied and siloed body of research across AI, wireless communication, and edge intelligence by suggesting a new taxonomy matched with key 6G functions: beamforming, mobility management, localisation, semantic transmission, and immersive control. Although CV greatly increases the adaptability and responsiveness of communication systems, our study reveals that its real-time implementation under URLLC constraints, together with problems of dataset scarcity, model explainability, and energy economy, still remains unresolved. Moreover, the growing dependence on distributed learning models such federated and split learning emphasises the necessity of privacy-preserving yet computationally reasonable CV pipelines. Looking ahead, we underlined several new trends including generative dataset synthesis, vision-assisted RIS control, swarm-based multi-agent vision, and sustainable edge-based CV inference. Complementing developments in digital twins, quantum perception, and metarobotics are these directions expected to define the next frontier of vision-native 6G systems. This work provides not only a reference for researchers but also a blueprint for designing intelligent 6G systems where communication and vision converge by aggregating present progress, spotting important gaps, and suggesting a disciplined research agenda.

Data Availability Statement

Data will be made available on request.

Funding

This work was supported by Scientific and Technological Research Council of Turkey (TUBITAK) under Grant 124E519.

Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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