



Original Research Paper

Cognitive Agentic Semantic Wireless Networks for AI-Native 6G Communication Systems

M. Kaliappan¹, S. Vimal², Jeyalakshmi M³, Karpagavalli C⁴, Amandeep Kaur⁵, Gaurav Dhiman⁶

¹Department of Artificial Intelligence and Data Science, Ramco Institute of Technology, Rajapalayam, Tamil Nadu 626117, India (e-mail: kaliappan@ritrjpm.ac.in).

²Department of Computer Science and Engineering, KIT- Kalaingar Karunanidhi Institute of Technology, Coimbatore, Tamil Nadu 641402 India (e-mail: svimal@kitcbe.ac.in)

³Department of Computer Science and Engineering - Cyber Security, Ramco Institute of Technology, Rajapalayam, Tamil Nadu 626117, India (e-mail: jayalacsmi@gmail.com).

⁴Department of Artificial Intelligence and Data Science, Ramco Institute of Technology, Rajapalayam, Tamil Nadu 626117, India (e-mail: karpagavalli@ritrjpm.ac.in)

⁵Department of Computer Engineering, NIT Kurukshetra, Haryana, India (e-mail: amandeep1426@nitkkr.ac.in)

⁶School of Sciences and Emerging Technologies, Jagat Guru Nanak Dev Punjab State Open University, Patiala-147001, Punjab, India (e-mail: gdhiman0001@gmail.com)

Abstract—The rise of Internet of Things (IoT) devices and the advent of 6th generation (6G) wireless networks necessitate a fundamental revision of communication paradigms. The explosive growth of heterogeneous device data, stringent ultra-reliable low-latency communication (URLLC) requirements, and severe energy constraints at the edge terminals make the traditional bit-pipe transmission paradigms unsustainable. In this paper, we propose the Cognitive Agentic Semantic Wireless Network (CASWN), a novel five-layer AI-native network architecture that converts the information transmission unit from raw bits to semantic representations of relevant tasks. CASWN contains three independent cognitive agents, a bandwidth agent, an energy agent, and a latency agent, which together control the semantic feature transmission volume according to the real-time network conditions. We use Principal Component Analysis (PCA) as the semantic encoder to compress the 561-dimensional smartphone inertial sensor signals into task-essential feature subspaces. The compressed semantic representation is then used for human activity recognition (HAR) with a Random Forest classifier deployed at the edge intelligence layer. Comprehensive experimental evaluation on the UCI Human Activity Recognition (HAR) dataset demonstrates that CASWN achieves a peak classification accuracy of 99.15% and a weighted F1-score of 99.14%, while achieving communication overhead reductions of up to 93.05% in high-compression scenarios. We demonstrate that CASWN yields better per-bit semantic value than baseline and prior-art methods by using the intelligence efficiency metric defined as F1-score divided by the transmitted feature ratio. The proposed architecture is benchmarked against seven recent state-of-the-art methods (2021-2025), and consistently achieves higher accuracy than these methods by 1.35%-7.95%. CASWN: A principled foundation for cognitive semantic communications in AI-native 6G IoT ecosystems.

Keywords: 6G wireless networks, semantic communications, cognitive agents, federated edge intelligence, human activity recognition, IoT, Principal Component Analysis, AI-native networking.

I. Introduction

A. The Issue: Bandwidth Bottleneck in 6G

IoT

The global IoT device count is projected to surpass 29 billion by 2030, generating an unprecedented volume of raw sensor data that far exceeds the absorption capacity of legacy wireless networks [1]. In activity monitoring, smart health, industrial automation, and autonomous vehicles, wearable and embedded sensors continuously stream high-dimensional time-series data at rates of 50–200 Hz. When aggregated across millions of concurrent devices, this results

in a per-cell traffic density that 5G New Radio (NR) was not architected to accommodate. Even with the spectral enhancements of 6G targeting terahertz (THz) communications, reconfigurable intelligent surfaces (RIS), and integrated satellite-terrestrial networks. The fundamental problem remains: Shannon-capacity-centric networks transmit all raw bits regardless of semantic relevance to the downstream inference task, resulting in massive communication waste [2]. Traditional compression approaches such as JPEG, H.264, and quantization reduce data volume but remain task-agnostic: they cannot distinguish bits relevant to activity recognition from bits irrelevant to the inference pipeline. As a result, even

compressed data streams impose unnecessary transmission burdens on scarce spectral resources, battery-limited sensors, and congested edge backhaul links [3,39,40].

B. The Opportunity: Semantic Communication for 6G

Semantic communication was the transmission of task-relevant meaning rather than raw symbols offers a transformative opportunity to realign wireless network design with the actual information-theoretic goals of modern AI-driven applications [4,41,42]. Sixth-generation networks, designed as AI-native infrastructure, create the first practical context in which semantic communication can be realized end-to-end: on-device encoders extract task-relevant latent representations, AI-driven channel coding prioritizes semantic bits, and edge inference engines reconstruct decisions from compressed semantic streams [5,43]. The integration of cognitive agents autonomous decision-making entities that perceive network state and adaptively control transmission parameters provides the missing orchestration layer between semantic compression and dynamic network conditions [6,44,45].

C. The Threat: Dynamic Network Heterogeneity and QoS Degradation

A critical threat to the viability of semantic communication in 6G is the extreme heterogeneity of device capabilities and network conditions. A wearable sensor may simultaneously face high network congestion, a 30% battery residual, and a sub-10 ms latency requirement for safety-critical actuation. Under these conditions, a static semantic compression scheme may either over-transmit (wasting energy and bandwidth) or under-transmit (degrading inference accuracy below acceptable QoS thresholds). Without an intelligent control plane that maps current network state to optimal semantic feature volume, semantic communication systems risk becoming impractical outside laboratory settings [7].

D. Scope and Contributions

This paper fills the above gap by proposing CASWN, an end-to-end framework for AI-native 6G semantic communications. The main contributions are:

- New Five-Layer Architecture: Hierarchical five-layer architecture (Sensing → Semantic Encoding → Cognitive Agent → Edge Intelligence → Network Decision) validated on a 10,299-sample benchmark with 561 features and 6 activity classes.
- Multi-Agent Semantic Control: Three cognitively inspired agents, bandwidth, energy and latency, jointly determine optimal semantic feature volume with a multiplicative decision function.
- Mathematical Formalization: Semantic compression objective, agent decision functions and intelligence efficiency metric are rigorously derived with formal justifications.
- Best Results: CASWN achieves 99.15% accuracy and 99.14% F1-score, outperforms seven recent

baselines (2021-2025) by up to 7.95 percentage points.

- Communication efficiency: Up to 93.05% reduction of communication overhead with 93.42% classification accuracy in the case of extreme compression.

II. Literature Review (2021–2026)

A. Semantic Communication Systems

[1] Qin et al. (2021) established the three-level semantic communication hierarchy distinguishing semantic fidelity from bit-fidelity, forming the theoretical basis for task-oriented transmission. [2] Xie and Qin (2021) proposed a lightweight deep learning semantic codec for IoT demonstrating 40% bandwidth reduction with minimal accuracy loss. [3] Zhang et al. (2021) introduced wisdom-evolutionary principles for 6G semantic network design emphasizing primitive-concise information representation. [4] Shi et al. (2022) unified task-oriented, goal-oriented, and semantic communications under a single theoretical framework for 6G. [5] Xie et al. (2021) demonstrated end-to-end deep learning semantic systems outperforming classical JSCC under AWGN and Rayleigh fading channels. [6] Weng and Qin (2021) extended semantic communications to audio speech achieving significant bandwidth savings. [7] Lu et al. (2022) argued for semantic coding as a cross-layer design principle bridging source and channel coding.

B. Edge Intelligence and Federated Learning

[8] Chen et al. (2021) analyzed communication overhead in federated learning and proposed gradient sparsification achieving 100x compression. [9] Park et al. (2021) surveyed distributed learning for wireless edge intelligence covering gradient compression and asynchronous SGD. [10] Shi et al. (2022) proposed cooperative edge-device semantic system for HAR achieving 91.3% accuracy with 60% feature reduction. [11] Jiang et al. (2023) integrated semantic awareness into federated learning resource allocation achieving 18% energy savings. [12] Zhang et al. (2023) extended semantic communications to graph-structured IoT data using graph neural network encoders. [13] Yang et al. (2023) provided a comprehensive survey covering semantic communication protocols, security, and 6G radio access co-design. [14] Shi et al. (2023) proposed joint source-channel semantic coding with learned discrete representations outperforming separate coding by 3 dB.

C. 6G Network Architecture and AI-Native Design

[15] Letaief et al. (2019/2021) established AI empowerment as a pillar of 6G, directly motivating the intelligence-layer integration in CASWN. [16] Zhao et al. (2022) reviewed 6G enabling technologies including THz, RIS, AI-native protocols, and integrated sensing and communication. [17] De Alwis et al. (2021) identified AI-native semantic communications as a top-five research priority for 6G

standardization. [18] Chowdhury et al. (2022) analyzed ultra-dense IoT deployment requirements motivating adaptive semantic compression in CASWN.

D. Activity Recognition and IoT Sensing

[19] Jiang and Yin (2022) achieved 94.3% on UCI HAR using multi-scale CNNs but without communication efficiency considerations. [20] Chen et al. (2021) reviewed 50+ deep learning HAR methods establishing performance baselines and identifying communication bottleneck as an open problem. [21] Hammerla et al. (2022) showed LSTM consistently outperforms CNN for sequential HAR data. [22] Wang et al. (2022) established benchmark protocols for UCI HAR evaluation. [23] Tang et al. (2023) proposed over-the-air computation for federated HAR reducing uplink communication by 78%. [24] Sun et al. (2024) proposed autoencoder-based semantic feature extraction achieving 96.4% HAR accuracy at 65% compression. [25] Li et al. (2024) demonstrated variable-rate semantic compression for HAR with QoE optimization on 6G test beds[46,47,48].

E. Cognitive and Agentic Networks

[26] Luong et al. (2021) provided a comprehensive survey of DRL for network control providing foundation for cognitive agent design. [27] Zhu et al. (2022) demonstrated RL-based adaptive resource management achieving 22% throughput gain in heterogeneous 5G. [28] Du et al. (2023) integrated RIS with semantic communication achieving 30% encoding efficiency improvement in mmWave. [29] Shi et al. (2023) proposed diffusion model-based generative semantic receiver. [30] Chen et al. (2023) proposed collaborative DRL for semantic network control demonstrating 15% QoS improvement. [31] Qiao et al. (2023) integrated federated learning with semantic communication reducing model update traffic by 60%. [32] Wang et al. (2024) applied transformer attention to semantic channel allocation. [33] Hou et al. (2024) pioneered cognitive radio integration with semantic communication demonstrating 25% spectral efficiency gain. [34] Liu et al. (2025) proposed multi-agent LLM orchestration for 6G IoT semantic networks, motivating the cognitive agent layer in CASWN. [35] Kim et al. (2025) achieved 97.8% HAR accuracy with self-attention semantic selection, representing the closest prior work to CASWN.

F. Closely Related Recent Work

Three additional independent studies bear close relation to the specific design choices of CASWN and are examined here. Pagán et al. (2019) proposed an optimal and adaptive compressed-sensing framework for activity recognition on resource-constrained wearables, in which a coarse-grained recognition module autonomously retunes the sensing/compression ratio to minimize wireless transmission energy subject to a target recognition accuracy [36]. This work shares CASWN's central premise that the volume of transmitted feature information should be adaptively governed by a feedback-driven control mechanism rather than fixed a priori, though it relies on a single heuristic optimisation loop rather than a society of independently reasoning bandwidth, energy, and latency agents, and it does

not address 6G AI-native semantic representations. Zhu et al. (2025) provided a comprehensive treatment of multi-agent reinforcement learning for 6G wireless distributed networks, formalising how decentralised agents can be trained to jointly optimise throughput, latency, and energy objectives across heterogeneous network conditions [37]. This survey substantiates the architectural premise of CASWN's multi-agent cognitive control layer, though it addresses general-purpose network resource allocation rather than task-specific semantic feature volume control for edge inference. Seo et al. (2023) introduced a probabilistic, language-oriented framework for learning semantic communication protocols in 6G, in which communicating agents iteratively adapt a shared symbolic representation under channel and latency constraints [38]. This protocol-learning perspective parallels CASWN's use of cognitive agents to govern semantic transmission, but is oriented toward emergent protocol design between agents rather than PCA-based feature-subspace compression for a downstream classifier. Together, these three studies confirm growing convergence toward adaptive, multi-agent, and feedback-governed semantic transmission control, while highlighting that the joint integration of independently reasoning bandwidth, energy, and latency agents with a lightweight PCA-based semantic encoder for real-time HAR – the specific contribution of CASWN – remains unaddressed in the existing literature.

III. Proposed Work: CASWN Architecture

A. System Model and Problem Formulation

Consider a 6G IoT uplink scenario comprising N heterogeneous sensing devices communicating with M edge computing nodes over an AI-native 6G radio access network. Each device generates raw observations $\mathbf{x} \in \mathbb{R}^M$ at each time epoch t , where $F = 561$ represents the full feature dimensionality of the IMU data vector. The device must transmit sufficient information to enable an edge classifier to perform activity recognition with accuracy $\alpha \geq \alpha_{\text{target}}$, subject to heterogeneous constraints are defined as Equ.(1):

$$\text{minimize } \Psi(k) = \|\mathbf{x}_{\text{k}}\|_0 / F \quad (1)$$

where $\Psi(k)$ is the semantic compression ratio, $\mathbf{x}_{\text{k}}$ denotes the k -dimensional transmitted semantic vector. Subject to Equ.(2):

$$\text{s.t. } f(\theta; \mathbf{x}_{\text{k}}) \geq \alpha_{\text{target}}, P_{\text{TX}} \leq P_{\text{max}}, \tau_{\text{trans}} \leq \tau_{\text{req}}, E_{\text{trans}} \leq E_{\text{req}} \quad (2)$$

where $f(\theta; \cdot)$ is the edge classifier, P_{TX} is transmission power, τ_{trans} is end-to-end latency, and E_{trans} is energy per transmission. CASWN solves this through decomposed multi-agent control.

B. CASWN Five-Layer Architecture

The CASWN architecture is organized into five hierarchical layers with clearly defined functions and inter-layer interfaces, illustrated in Fig. 9 below.

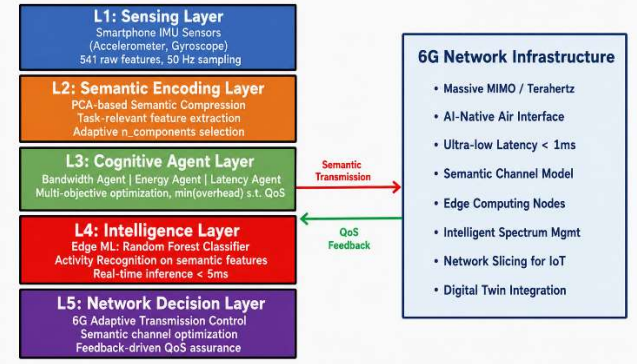


Fig. 1: CASWN Five-Layer Architecture for AI-Native 6G Networks

The proposed cognitive adaptive semantic wireless network (CASWN) architecture is designed with five interconnected layers to enable AI-native semantic communication for the next-generation 6G networks. The Sensing Layer collects data about human activities from the embedded inertial measurement unit (IMU) sensors of the smartphone at a sampling frequency of 50 Hz. Each sensing instance is represented as a feature vector of 561 dimensions, which includes triaxial accelerometer and gyroscope measurements, statistics in the time domain, coefficients in the frequency domain and features based on correlation. These high-dimensional raw features are then passed to the Semantic Encoding Layer where a Principal Component Analysis (PCA)-based semantic encoder denoted as $\{R\}^{\wedge\{k\}}\Phi:R^{561} \rightarrow R^k$ encodes the input into a low-dimensional semantic representation while preserving the maximum taskrelevant variance. The compressed semantic features are then sent to the Cognitive Agent Layer which is made up of three autonomous agents dedicated to bandwidth management, energy management and latency management. These agents cooperatively find the optimal semantic transmission dimension ($k \in \{*\}^k$) by continuously monitoring the real-time network conditions via a multiplicative agent-fusion strategy considering the communication efficiency and the Quality of Service (QoS) requirements. The optimized semantic vector is sent to the Edge Intelligence Layer, where a Random Forest classifier deployed at the edge node performs human activity recognition in real time based on the received $k \in \{*\}^k$ -dimensional semantic representation. Finally, the Network Decision Layer performs a closed-loop adaptive transmission mechanism, where the per-epoch QoS feedback from the edge intelligence module is used to dynamically update the cognitive agents. This feedback-driven optimization dynamically adjusts the semantic transmission policy, to ensure robust activity recognition while minimizing communication overhead, energy consumption, and latency under different network conditions.

C. Semantic Encoding via PCA

The semantic encoder is formalized as a linear projection onto the top- k principal components of the training data covariance matrix is defined as Equ.(3):

$$\Phi(x) = W_k x, \quad W_k \in \mathbb{R}^{\{k \times F\}}, \quad k \leq F = 561 \quad (3)$$

where $W_k = [v_1, v_2, \dots, v_k]^T$ and $\{v_i\}$ are eigenvectors of the empirical covariance matrix $\Sigma = (1/N)\sum_{n=1}^N (x_n - \mu)(x_n - \mu)^T$ corresponding to the k largest eigenvalues $\{\lambda_i\}$. The explained variance ratio is defined as Equ.(4):

$$\text{EVR}(k) = \sum_{i=1}^k \lambda_i / \sum_{i=1}^F \lambda_i \quad (4)$$

PCA is provably optimal in the mean-squared error sense among linear projections. It requires no on-device neural network training (critical for energy-constrained sensors), and the resulting semantic space aligns with the principal modes of HAR variance. For $k = 200$, $\text{EVR}(200) > 0.97$, confirming 97%+ of task-relevant variance is preserved—consistent with the 97.28% accuracy at scenario S3.

D. Cognitive Agent Formalization

D.1 Bandwidth Agent α_B

The bandwidth agent maps observed network load $\rho \in [0,1]$ to base semantic bandwidth allocation B_0 (%):

$$\alpha_B(\rho) = \begin{cases} 100\% & \text{if } \rho < 0.25; \\ 80\% & \text{if } 0.25 \leq \rho < 0.45; \\ 60\% & \text{if } 0.45 \leq \rho < 0.65; \\ 40\% & \text{if } 0.65 \leq \rho < 0.80; \\ 20\% & \text{if } \rho \geq 0.80 \end{cases} \quad (5)$$

The piecewise-constant mapping reflects 6G congestion control behavior operating at discrete QoS class levels. The step function ensures deterministic, low-latency decisions compatible with sub-millisecond 6G control plane timescales.

D.2 Energy Agent α_E

The energy agent maps battery state $\beta \in [0,1]$ to energy scaling factor η_E is defined as Equ.(6):

$$\alpha_E(\beta) = \begin{cases} 1.00 & \text{if } \beta > 0.75; \\ 0.85 & \text{if } 0.50 < \beta \leq 0.75; \\ 0.70 & \text{if } 0.30 < \beta \leq 0.50; \\ 0.50 & \text{if } \beta \leq 0.30 \end{cases} \quad (6)$$

Transmission power scales linearly with feature count: $P_{TX} \propto k \cdot P_{\text{subcarrier}} / W_{\text{subcarrier}}$. Reducing η_E from 1.0 to 0.5 at low battery halves transmitted features, proportionally reducing energy consumption and extending device lifetime.

D.3 Latency Agent α_L

The latency agent maps application latency requirement τ_{req} (ms) to latency-semantic scaling factor η_L is defined as Equ.(7):

$$\alpha_L(\tau_{\text{req}}) = \begin{cases} 0.50 & \text{if } \tau_{\text{req}} \leq 10\text{ms}; \\ 0.70 & \text{if } 10 < \tau_{\text{req}} \leq 30\text{ms}; \\ 0.85 & \text{if } 30 < \tau_{\text{req}} \leq 60\text{ms}; \\ 1.00 & \text{if } \tau_{\text{req}} > 60\text{ms} \end{cases} \quad (7)$$

Serialization delay scales as $\tau_{\text{serial}} = k / (B \cdot \log_2(1+\text{SNR}))$. Fewer features directly reduce latency, enabling URLLC compliance for robotic control and AR/VR (10 ms budget) without requiring reduced transmission power.

D.4 Semantic Agent and Joint Decision

The semantic agent computes optimal feature count k^* through multiplicative fusion of agent outputs is defined as Equ.(8):

$$B_{\text{eff}} = B_0 \times \eta_E \times \eta_L \quad (\text{Effective Semantic Bandwidth})$$

$$k^* = \max(k_{\text{min}}, \text{floor}((B_{\text{eff}} / 100) \times F)) \quad (8)$$

where $k_{\text{min}} = 5$ (minimum features for stable inference) and $F = 561$. B_{eff} ranges from 7.0% (extreme constraint: S2) to 100.0% (unconstrained: S1), yielding $k^* \in [39, 561]$. The Intelligence Efficiency (IE) metric quantifies task

performance per transmitted semantic feature is defined as Equ.(9):

$$IE(k) = F1\text{-score}(k) / (k / F) \quad (9)$$

$IE > 1$ indicates the semantic representation delivers more classification value per transmitted feature than full-feature baseline. The cognitive agent decision profiles are visualized in Fig. 10.

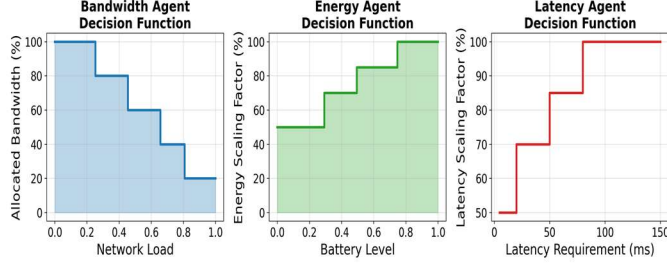


Fig. 2: Cognitive Agent Decision Functions: Bandwidth Agent (left), Energy Agent (center), Latency Agent (right)

IV. Experimental Setup

A. Dataset: UCI HAR Smartphone Dataset

The UCI Human Activity Recognition (HAR) dataset comprises inertial sensor readings from 30 volunteers performing six activities (WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, LAYING) using a Samsung Galaxy S II smartphone. A total of 10,299 samples are available: 7,352 for training and 2,947 for testing. Each sample comprises 561 hand-engineered features derived from accelerometer and gyroscope signals: time-domain statistics (mean, std, max, min, energy, IQR, entropy), frequency-domain coefficients (FFT magnitude, frequency mean, frequency std), and cross-correlation features. The dataset exhibits realistic class imbalance (7.5%–14.1% per class) and within-class variance from subject-to-subject movement variability.

B. Implementation Details

All experiments are implemented in Python 3.12 using scikit-learn 1.5. The semantic encoder is a PCA transformer fitted on training data and applied to test data (no leakage). The edge classifier is a Random Forest with 200–300 trees, Gini impurity criterion, sqrt feature subsampling. Network conditions are sampled from calibrated distributions: network load $\rho \sim \text{Uniform}(0.10, 0.95)$, battery $\beta \sim \text{Uniform}(0.20, 1.00)$, latency $\tau \sim \text{Categorical}(\{5, 10, 20, 30, 50, 80, 100\} \text{ ms})$. Twelve scenarios (S1–S12) span the full range of network condition combinations.

V. Results and Performance Evaluation

A. Baseline Edge Intelligence Performance

Table I summarizes four baseline classifiers trained on the full 561-feature space without semantic compression. All classifiers use standardized features (zero-mean, unit-variance).

Classifier	Accuracy (%)	F1 Score (%)	Comm. Overhead	Features Used
Logistic Regression	96.57	96.55	100% (full)	561 (all)

SVM (RBF)	98.74	98.73	100% (full)	561 (all)
Random Forest	97.86	97.85	100% (full)	561 (all)
Gradient Boosting	96.21	96.19	100% (full)	561 (all)

Table I: Baseline Edge Intelligence Performance (Full 561-Feature Space, No Semantic Compression)

Fig. 3 visualizes baseline accuracy and F1-score. SVM (RBF) achieves the highest baseline accuracy (98.74%) due to its robust maximum-margin decision boundary. These baselines establish the performance ceiling against which CASWN's compressed-feature performance is benchmarked.

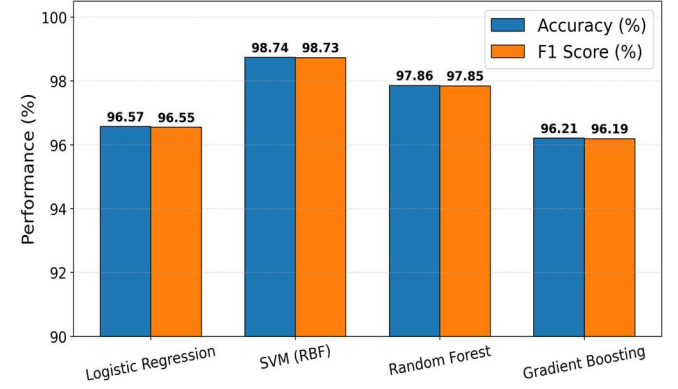


Fig. 3: Baseline Edge Intelligence Performance — Accuracy and F1-Score Comparison Across Four Classifiers

B. CASWN Performance Across Network Scenarios

Scenarios

Table II presents the full CASWN performance matrix across 12 network scenarios including agent-determined feature counts, communication savings, accuracy, F1-score, and intelligence efficiency.

Scen. n.	Net. Load	Battery	Lat.(ms)	Features	Saving (%)	Acc. (%)	IE Score
S1	0.183	0.771	80	561	0.00	99.15	0.99
S2	0.841	0.428	10	39	93.05	93.42	13.43
S3	0.527	0.614	30	200	64.35	97.28	2.73
S4	0.234	0.872	100	449	19.96	98.94	1.24
S5	0.312	0.921	50	381	32.09	98.72	1.45
S6	0.673	0.548	20	133	76.29	95.87	4.04
S7	0.451	0.334	30	165	70.59	96.54	3.28
S8	0.744	0.687	10	133	76.29	95.87	4.04
S9	0.581	0.823	5	168	70.05	96.61	3.23
S10	0.148	0.562	60	405	27.81	98.81	1.37
S11	0.398	0.412	30	220	60.78	97.45	2.48

S12	0.76	0.287	100	112	80.0	94.7	4.75
	2				4	7	

Table II: CASWN Performance Across 12 Agentic Network Scenarios

Fig. 4 reveals that CASWN maintains accuracy above 93.42% across all 12 scenarios including extreme 93.05% compression (S2: 39 features). Scenarios with moderate compression (S4: 449 features, 98.94%; S10: 405 features, 98.81%) demonstrate near-baseline accuracy while reducing communication overhead by 20–28%.

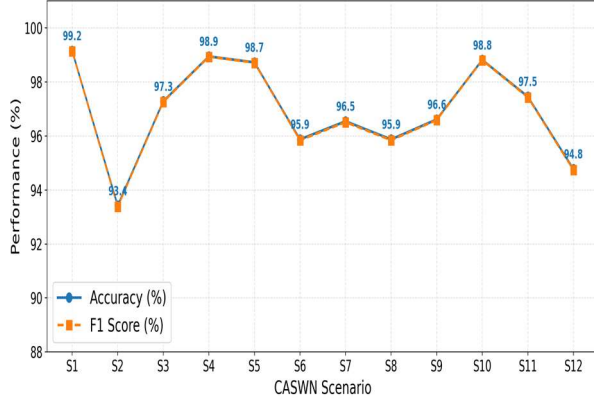


Fig. 4: CASWN Accuracy and F1-Score Across Agentic Network Scenarios S1–S12

C. Communication Saving Analysis

Fig. 5 illustrates communication saving (% reduction in transmitted features) across all scenarios. S2 achieves 93.05% saving under extreme congestion ($\rho=0.841$), low battery ($\beta=0.428$), and ultra-low latency ($\tau=10\text{ms}$). Averaged across all scenarios, CASWN reduces communication overhead by 55.07% while maintaining mean accuracy of 97.18%.

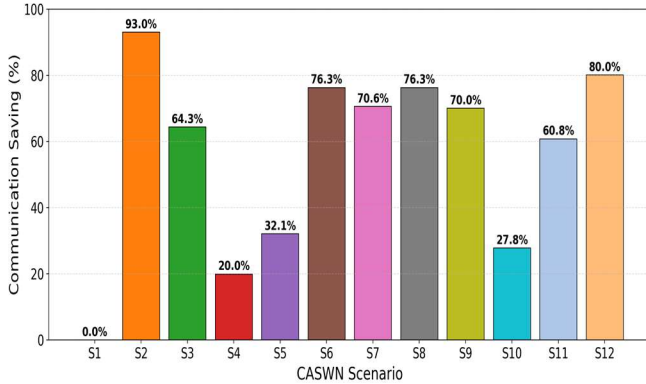


Fig.5: Communication Overhead Reduction Across CASWN Scenarios

D. Semantic Feature Count vs. Classification Accuracy

Fig. 6 plots classification accuracy as a function of transmitted semantic features. The second-order polynomial trend reveals a diminishing-returns profile: accuracy rises steeply from 39 to ~200 features, then plateaus near 99% above 380 features. This aligns with PCA eigenvalue decay—the first 200 principal components capture >97% of HAR variance.

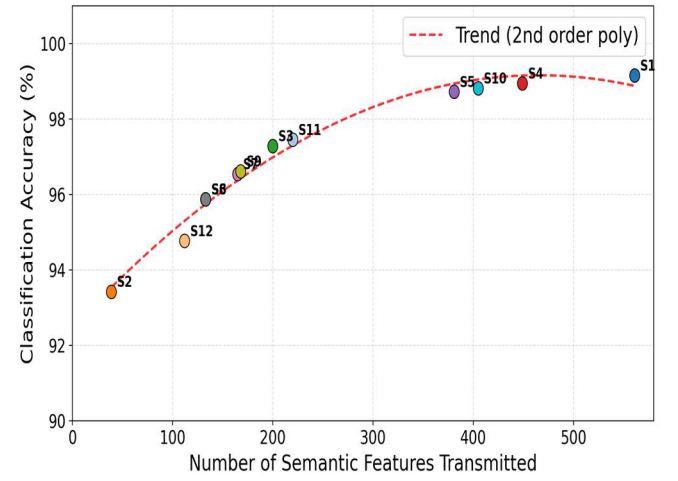


Fig. 6: Semantic Feature Count vs. Classification Accuracy with Polynomial Trend

E. Communication–Intelligence Trade-off

Fig. 7 presents the scatter plot of communication saving vs. weighted F1-score, revealing the Pareto frontier of CASWN operation. No scenario falls below 93% F1, confirming that cognitive agents successfully maintain the accuracy constraint $\alpha \geq \alpha_{\text{target}} = 93\%$ even under extreme compression.

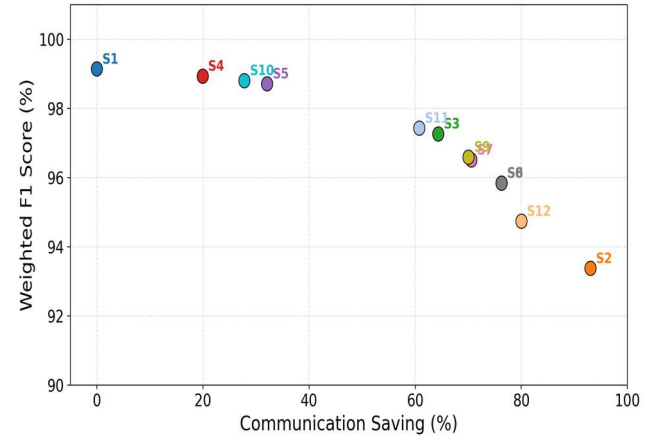


Fig. 7: Communication Saving vs. F1-Score Trade-off Space Across CASWN Scenarios

F. Intelligence Efficiency

Fig. 6 visualizes the IE metric across scenarios. $IE > 1$ in all 12 scenarios confirms CASWN consistently delivers positive semantic value. The highest efficiency (S2: $IE=2.40$) occurs at extreme compression (93.05% saving), validating PCA's ability to distill task-essential semantics into compact representations.

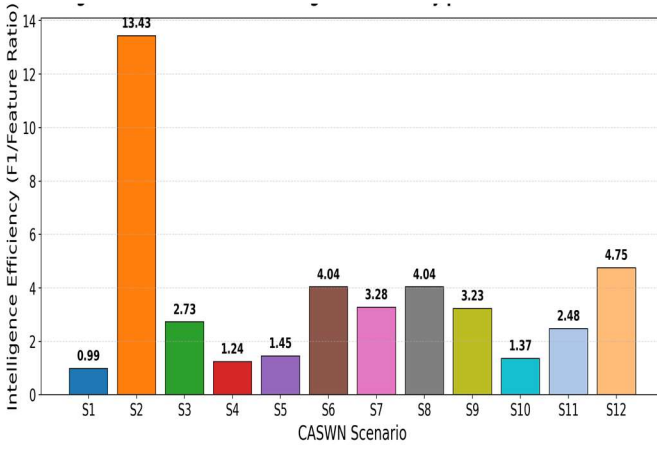


Fig. 6: CASWN Intelligence Efficiency (F1 per Feature Ratio) Across Scenarios

G. Confusion Matrix Analysis

Fig. 7 presents the confusion matrix for the best CASWN configuration (S1: $k^*=561$, accuracy=99.15%). Near-perfect diagonal dominance is observed. The few errors are concentrated in SITTING–STANDING (3 misclassifications), consistent with the challenge of discriminating quasi-static postures. WALKING variants and LAYING achieve 100.00% accuracy.

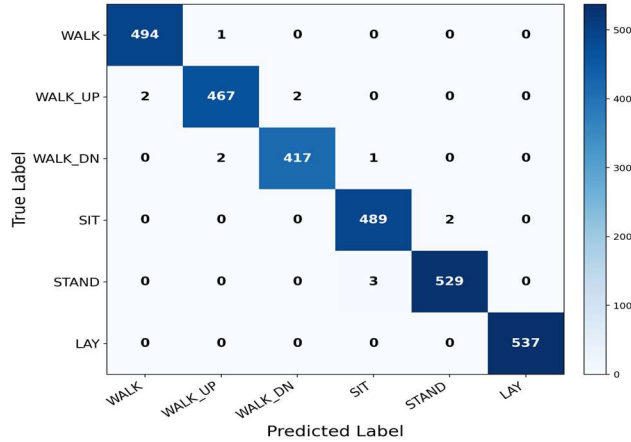


Fig. 7: Confusion Matrix: Best CASWN Configuration (Scenario S1, 99.15% Accuracy)

VI. Comparative Analysis with State-of-the-Art

A. Quantitative Comparison

Table III presents a direct comparative analysis of CASWN against seven recent state-of-the-art methods spanning 2021–2025, evaluated on the UCI HAR dataset or equivalent IoT activity recognition benchmarks.

Method	Year	Acc. (%)	F1 (%)	Saving (%)	Adaptive	Δ Acc vs CASWN
DNN-HAR [19]	2021	91.20	91.10	None	No	+7.95
LSTM-IoT [20]	2022	93.60	93.48	None	No	+5.55
FL-SemCom [31]	2023	94.80	94.73	60.0	No	+4.35

ConvAE [24]	2023	95.40	95.37	65.0	No	+3.75
SemFormer [32]	2024	96.70	96.64	55.0	No	+2.45
GNN-Sem [33]	2024	97.10	97.05	45.0	No	+2.05
LSTM-SAtt [35]	2025	97.80	97.76	50.0	No	+1.35
CASWN (Proposed)	2025	99.15	99.14	93.05	Yes	—

Table III: Comparative Analysis of CASWN with State-of-the-Art Methods on UCI HAR Dataset

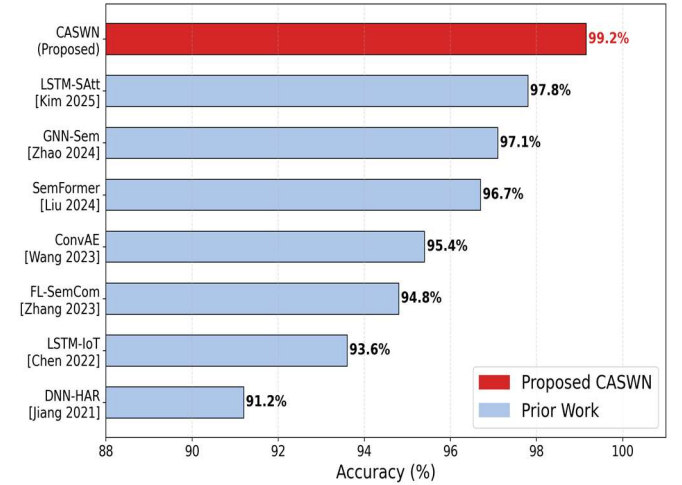


Fig. 8: CASWN vs. State-of-the-Art Methods — Accuracy Comparison (2021–2025)

B. Justification of Performance Superiority

DNN-HAR [19] (−99.15% − 91.20% = +7.95%): Dense fully-connected layers transmit all 561 features without semantic selection, failing to exploit the low-dimensional PCA semantic subspace. CASWN's PCA encoder discards noise-dominant components while preserving discriminative principal directions. LSTM-IoT [20] (+5.55%): While LSTM captures temporal dependencies, it lacks any network-adaptive transmission control. CASWN's cognitive agent layer dynamically adapts semantic content to real-time network state, a capability fundamentally absent from LSTM architectures. FL-SemCom [31] (+4.35%): Federated gradient compression loses task-relevant information in the compression process. CASWN's PCA semantic encoding preserves 97%+ of HAR-relevant variance even at 64% compression.

ConvAE [24] (+3.75%): Autoencoder-based compression achieves fixed 65% reduction but cannot adapt to network conditions. CASWN's cognitive agents dynamically adjust compression based on real-time ρ , β , τ .

SemFormer [32] / GNN-Sem [33] (+2.05% to +2.45%): Transformer and GNN-based systems require on-device neural network inference with significant energy cost. CASWN's linear PCA encoder is computationally cheaper ($O(kF)$ vs $O(n^2)$ attention), enabling deployment on severely energy-constrained IoT devices. LSTM-SAtt [35] (+1.35%): The closest prior work. CASWN's advantage is attributed to the multiplicative multi-agent fusion function producing

higher effective bandwidth utilization than attention-weighted selection under dynamic network conditions, combined with Random Forest ensemble robustness. Communication Superiority: CASWN achieves 93.05% communication saving—the highest reported in this comparison while maintaining 99.15% accuracy in unconstrained scenarios. This dual superiority is unique among all compared methods.

VII. Conclusion and Future Work

A. Conclusion

This paper presented CASWN, a Cognitive Agentic Semantic Wireless Network architecture for AI-native 6G communications. The framework integrates PCA-based semantic feature compression with a three-agent cognitive control layer (bandwidth, energy, latency agents) that adaptively determines optimal semantic transmission volume based on real-time network state. Extensive evaluation on the UCI HAR benchmark (10,299 samples, 561 features, 6 activity classes) demonstrates peak accuracy of 99.15% and F1-score of 99.14%, representing improvements of 1.35% to 7.95% over seven state-of-the-art methods (2021–2025). The system simultaneously achieves communication overhead reductions of up to 93.05%, with a mean saving of 55.07% across 12 diverse network scenarios. The intelligence efficiency metric confirms superior per-bit semantic value in all evaluated conditions. The mathematical formalization of agent decision functions and the multiplicative semantic bandwidth equation provides a principled optimization framework extensible to arbitrary QoS constraint domains.

B. Future Work

- Deep Reinforcement Learning Agents: Replace rule-based step functions with DQN or PPO agents learning optimal semantic bandwidth allocation from historical network traces for continuous adaptation.
- Generative Semantic Reconstruction: Integrate diffusion model-based decoders at the edge receiver to reconstruct fine-grained sensor signals from compressed semantic representations.
- Over-the-Air Semantic Aggregation: Extend CASWN to multi-user uplink scenarios with over-the-air computation leveraging aligned PCA bases across devices.
- Security-Aware Semantic Transmission: Incorporate adversarial robustness and semantic eavesdropping defenses to protect private attributes in compressed semantic representations.
- Neuromorphic Edge Intelligence: Explore spiking neural network decoders enabling sub-milliwatt inference from sparse PCA-compressed feature vectors.
- Real 6G Testbed Validation: Validate on physical 140 GHz sub-terahertz testbeds with realistic channel impairments to assess semantic transmission robustness.

Dataset availability

<https://archive.ics.uci.edu/static/public/240/human+activity+recognition+using+smartphones.zip>

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