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APPLICATION OF MACHINE LEARNING ALGORITHMS FOR AUTOMATIC MODULATION CLASSIFICATION OF RADIO SIGNALS

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Introduction and Problem Relevance. The rapid advancement of modern wireless telecommunications, the exponential increase in Internet of Things (IoT) devices, and the intensive utilization of electromagnetic spectrum have led to unprecedented congestion in the radio frequency environment. In contemporary civilian and tactical radio communications, cognitive radio systems, and electronic surveillance, radio environments are characterized by high signal density, non-cooperative transmissions, dynamic frequency sharing, and severe channel distortions. Under these conditions, the receiver often possesses no prior knowledge regarding the parameters of incoming emissions, such as carrier frequency, symbol rate, pulse-shaping filters, or modulation scheme.

Automatic Modulation Classification (AMC) functions as a crucial intermediate processing step situated between signal detection and subsequent demodulation or intelligence analysis. Traditional demodulators require exact knowledge of the modulation type to configure matched filters and recovery loops. AMC algorithms enable non-cooperative receivers, cognitive transceivers, and spectrum monitoring stations to recognize transmitted signal formats autonomously. Achieving real-time, highly accurate modulation identification under hostile propagation conditions-characterized by low Signal-to-Noise Ratio (SNR), fading channels, and active jamming-is a foundational requirement for modern electronic communications and radio intelligence.

Limitations of Conventional Approaches. Historically, AMC algorithms have been categorized into two principal methodologies: Likelihood-Based (LB) decision approaches and Feature-Based (FB) pattern recognition techniques. Likelihood-based methods, including the Average Likelihood Ratio Test (ALRAT), Generalized Likelihood Ratio Test (GLRT), and Hybrid Likelihood Ratio Test (HLRT), treat modulation classification as a formal composite hypothesis testing problem. While LB techniques are theoretically optimal in the sense of minimizing classification error probability in additive white Gaussian noise (AWGN) channels, they exhibit severe computational complexity. The evaluation of multi-dimensional likelihood functions requires intensive numerical integration over unknown parameters such as phase jitter, timing offsets, and channel gains, rendering real-time execution intractable on embedded receivers. Furthermore, LB algorithms suffer from extreme sensitivity to channel modeling mismatches.

Conversely, feature-based methods extract hand-crafted expert statistical features from intercepted signals and utilize classical decision trees, spectral thresholding, or shallow classifiers (such as support vector machines or k-nearest neighbors). Key extracted descriptors include instantaneous amplitude, instantaneous phase, instantaneous frequency, higher-order statistics (HOS), and cyclic cumulants (such as fourth- and sixth-order cumulants C40, C42, and C63). Although FB algorithms offer significantly reduced computational complexity compared to likelihood formulations, their diagnostic reliability degrades abruptly

at low SNR regimes (below 0 dB). Moreover, hand-crafted features are highly susceptible to carrier frequency offsets (CFO), symbol timing jitter, and non-stationary multipath fading, demanding extensive domain expertise and manual recalibration for every newly introduced modulation format.

Deep Learning Framework and Data Representation. Over the past decade, the paradigm of Machine Learning (ML), and specifically Deep Learning (DL), has transformed digital signal processing by replacing manual feature engineering with automated, hierarchical feature extraction directly from empirical data. In deep AMC architectures, neural networks learn optimal invariant representations straight from intercepted digitized radio waveforms. The performance of deep learning AMC is intrinsically linked to the domain representation of input radio signals.

Three primary signal representation formats are widely employed in machine learning pipelines: raw time-domain In-phase and Quadrature (I/Q) complex sequences, time-frequency distributions, and spatial constellation diagrams. Raw I/Q data representation forms a two-dimensional tensor of dimensions $2 \times N$, preserving complete amplitude and phase trajectory information without information loss caused by heuristic pre-processing. Time-frequency representations, obtained via the Short-Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT), or Wigner-Ville Distribution (WVD), map non-stationary radio signals into two-dimensional spectral images, highlighting instantaneous spectral energy transitions. Constellation diagrams map clustered complex symbol points onto the complex plane, allowing computer vision models to exploit geometric cluster symmetry characteristic of phase-shift keying (PSK) and quadrature amplitude modulation (QAM).

Architectural Analysis of Deep Neural Networks. Various deep neural network architectures demonstrate distinct inductive biases when processing digitized radio signals. Convolutional Neural Networks (CNN) have emerged as the foundational architecture for modulation classification. When applied to raw I/Q sequences, one-dimensional convolutional filters act as adaptive finite impulse response (FIR) filter banks, automatically synthesizing optimal filtering operations to isolate carrier harmonics, phase transitions, and modulation envelopes. Deep CNN architectures with residual skip connections (ResNet) mitigate the vanishing gradient problem, enabling the extraction of multi-scale abstract features. For two-dimensional time-frequency spectrograms and constellation images, deep 2D CNNs extract shift-invariant spatial patterns, demonstrating robust classification capabilities across analog (AM-DSB, AM-SSB, WFM) and digital (BPSK, QPSK, 8PSK, 16QAM, 64QAM, GFSK, CPFSK) schemes.

Recurrent Neural Networks (RNN), including Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU), are exceptionally well-suited for modeling temporal dynamics and sequential context across successive symbol intervals. While CNNs excel at extracting localized waveform patterns, recurrent networks capture long-range temporal dependencies and phase continuity inherent to continuous-phase modulations and differential encoding schemes. However, recurrent architectures exhibit higher computational latency due to sequential processing bottlenecks.

To synthesize the complementary strengths of spatial filtering and temporal sequence modeling, Convolutional Long Short-Term Deep Neural Networks (CLDNN) integrate cascading convolutional layers, recurrent layers, and fully connected dense layers into a unified pipeline. The front-end convolutional layers perform dimensionality reduction and spatial feature extraction from I/Q sequences, intermediate LSTM layers track sequential symbol transitions over time, and terminal dense layers perform softmax modulation classification. In this pipeline, front-end convolutional layers reduce dimensionality and extract spatial features from I/Q sequences. Subsequently, intermediate LSTM layers capture temporal symbol transitions, while terminal dense layers execute softmax modulation classification. Furthermore, modern Transformer architectures based on multi-head self-attention mechanisms are increasingly adopted, computing global pairwise correlations across all time samples in a signal burst and demonstrating superior resilience against burst interference and localized fading dips.

Robustness, Generalization, and Practical Implementation. The operational deployment of machine learning models in real-world radio environments requires addressing critical generalization challenges. Practical wireless propagation is plagued by physical channel impairments, including Rayleigh and Rician multipath fading, Doppler frequency spreading, Carrier Frequency Offset (CFO) caused by local oscillator instability, and Sampling Rate Offset (SRO) resulting from analog-to-digital converter clock drift. When

deep models are trained exclusively on idealized synthetic datasets (such as AWGN-only channels), their classification performance degrades severely when confronted with physical hardware non-idealities.

To ensure robust generalization, modern training pipelines incorporate comprehensive data augmentation strategies, injecting stochastic CFO shifts, phase rotations, Rayleigh fading profiles, and additive colored noise during the training cycle. Furthermore, domain adaptation techniques and adversarial training frameworks enable neural networks to map radio signals from diverse propagation environments into a shared, domain-invariant latent feature space.

From an implementation standpoint, deploying deep AMC algorithms on Software-Defined Radio (SDR) platforms (e.g., USRP, HackRF) and tactical edge devices necessitates stringent adherence to size, weight, power, and cost (SWaP-C) constraints. High-parameter deep models require significant memory bandwidth and computational throughput. Consequently, model optimization techniques-including INT8 post-training quantization, structural network pruning, and knowledge distillation from large teacher networks into lightweight student models-are vital. These techniques enable real-time inference latencies on the order of several milliseconds on embedded tensor accelerators (such as NVIDIA Jetson or FPGA-based neural processing units) without compromising classification fidelity.

Conclusions. 1. Machine learning and deep neural network algorithms provide a transformative methodology for Automatic Modulation Classification, overcoming the prohibitive computational overhead of likelihood-based tests and the sensitivity of hand-crafted feature-based methods under severe channel impairments.

2. Hierarchical deep architectures-specifically Residual CNNs, CLDNN hybrids, and Self-Attention Transformers-demonstrate superior classification performance directly on raw I/Q time-series samples and time-frequency distributions, achieving robust discrimination across complex analog and digital modulation schemes at low Signal-to-Noise Ratios.

3. Successful operational deployment in cognitive radio, electronic intelligence, and special communication systems hinges on training with augmented non-ideal channel conditions and applying model compression techniques (quantization and pruning) to satisfy strict real-time SWaP-C requirements on embedded software-defined radio platforms.

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ПРОГНОЗУВАННЯ ВРОЖАЙНОСТІ КУКУРУДЗИ НА ОСНОВІ БАЙЄСОВСЬКОЇ МЕРЕЖІ З ВИКОРИСТАННЯМ ЕКСПЕРТНИХ ОЦІНОК

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Сучасне сільськогосподарське виробництво залежить від сукупного впливу погодних, ґрунтових та агротехнологічних факторів. Оскільки врожайність сільськогосподарських культур формується під дією багатьох взаємопов’язаних чинників, її прогнозування в умовах невизначеності є складним