

Article

Not peer-reviewed version

Quantum Microwave Illumination Protocols Enhancing Low-Power Radar Detection in Noisy Wireless Environments

[Meenalochini Pandi](#) *

Posted Date: 28 January 2026

doi: 10.20944/preprints202601.2156.v1

Keywords: microwave quantum illumination; entanglement distribution; low-power detection; sum-frequency generation; Josephson parametric amplifiers; quantum-enhanced radar



Preprints.org is a free multidisciplinary platform providing preprint service that is dedicated to making early versions of research outputs permanently available and citable. Preprints posted at Preprints.org appear in Web of Science, Crossref, Google Scholar, Scilit, Europe PMC.

Copyright: This open access article is published under a [Creative Commons CC BY 4.0 license](#), which permit the free download, distribution, and reuse, provided that the author and preprint are cited in any reuse.

Disclaimer/Publisher's Note: The statements, opinions, and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions, or products referred to in the content.

Article

Quantum Microwave Illumination Protocols Enhancing Low-Power Radar Detection in Noisy Wireless Environments

Meenalochini Pandi

Department of Electrical and Electronics Engineering, Sethu Institute of Technology, Virudhunagar, India;
meenalochinip@gmail.com

Abstract

Microwave quantum illumination (QI) represents a paradigm shift in low-power wireless radar detection, leveraging entanglement between signal and idler microwave photons to achieve detection performance exceeding classical limits by up to 6 dB in error exponent, particularly in high-noise environments where traditional coherent radars falter. This comprehensive survey delineates the theoretical foundations and practical protocols of microwave QI, beginning with two-mode squeezed vacuum state generation using Josephson parametric amplifiers in cryogenic setups, which produce highly correlated photon pairs resilient to channel decoherence. Receiver architectures, including optical parametric amplifier-single-photon avalanche diode (OPA-SPADE) systems with sum-frequency generation for joint measurements and digital phase-conjugation for computational correlation recovery, enable efficient extraction of quantum discord even after significant atmospheric loss or low target reflectivity (under 1%). Performance analyses under realistic thermal noise models ($\bar{n} \gg 1$) and η -loss channels confirm sustained quantum advantages via the quantum Chernoff exponent ξ_Q , validated by ray-tracing simulations showing doubled detection range at fixed power and lab experiments at 10 GHz carriers detecting weak reflectors amid 100 K noise. Low-power optimizations such as adaptive entanglement tuning, chirped pulse shaping, and neural network-aided parameter selection yield 50% energy reductions without sacrificing fidelity, making QI viable for battery-limited platforms. Applications encompass short-range automotive/UAV radar for fog-penetrating obstacle avoidance, non-invasive biomedical subsurface imaging with safe radiation levels, covert perimeter security against jamming, and seamless integration into 6G networks via joint communication-sensing waveforms at mm Wave/THz bands. The paper identifies key challenges including multi-target scalability, real-time gigascale processing, and quantum RF interface standardization, proposing hybrid quantum-classical frameworks and entanglement-swapped sensor arrays as pathways to deployment. This work bridges quantum optics with RF engineering, equipping researchers with blueprints for prototyping transformative quantum-enhanced wireless sensing systems.

Keywords: microwave quantum illumination; entanglement distribution; low-power detection; sum-frequency generation; Josephson parametric amplifiers; quantum-enhanced radar

1. Introduction

Traditional low-power radar systems encounter severe performance degradation in cluttered, noisy wireless environments, as shot noise and thermal interference mask weak target echoes, especially under stringent power constraints vital for battery-operated platforms such as unmanned aerial vehicles and wearable sensors [1]. Microwave quantum illumination (QI) emerges as a transformative solution, drawing from quantum information theory to employ entangled microwave photon pairs generated via Josephson parametric amplifiers in superconducting circuits cooled to millikelvin temperatures. In this protocol, the signal photon transmits through lossy channels toward

low-reflectivity targets (often below 1%), while the idler photon stores locally, allowing post-return joint quadrature measurements that exploit persistent quantum discord for superior target discrimination against background thermal states [2].

Theoretical foundations, including the quantum Chernoff bound, predict asymptotic error probability reductions outperforming optimal classical strategies by up to 6 dB in high-noise regimes ($\bar{n} \gg 1$), with recent microwave experiments confirming practical feasibility at 10 GHz carriers amid 100 K noise equivalents [3]. This motivation intensifies for beyond-5G networks demanding integrated sensing-communication, where QI enables robust, spectrum-efficient detection without power hikes, addressing critical gaps in autonomous systems and secure perimeters.

1.1. Motivation and Background

The pressing need for low-power radar stems from escalating demands in dense wireless ecosystems, where spectrum scarcity and energy limits curtail classical coherent detection relying on strong signal-to-noise ratios vulnerable to multipath fading and jamming [4]. Microwave QI fundamentally alters this landscape by leveraging non-classical two-mode squeezed vacuum states, where exponential photon-number correlations between signal and idler modes persist through η -loss channels ($\eta < 0.1$), enabling error exponents ξ_Q that exceed classical ξ_C via residual entanglement or discord. Historical evolution traces from optical quantum illumination proposals to microwave adaptations using circuit quantum electrodynamics, with breakthroughs like digital phase-conjugation receivers demonstrating real-time correlation recovery without upconversion losses [5].

Background noise models incorporating Gaussian thermal baths underscore QI's resilience, as idler-conditional signal statistics reject clutter more effectively than direct imaging, achieving doubled detection ranges in urban simulations at fixed milliwatt powers [6]. This paradigm shift motivates interdisciplinary fusion of quantum optics, RF engineering, and signal processing, targeting applications from fog-penetrating automotive radar to noninvasive biomedical tissue imaging, where radiation safety mandates minimal transmit energies. By circumventing the standard quantum limit, QI positions itself as a cornerstone for quantum-enhanced 6G, promising unprecedented sensitivity in contested environments [7].

1.2. Scope and Contributions

This article confines its analysis to microwave QI protocols explicitly tailored for wireless radar detection, encompassing state preparation, channel propagation, receiver optimization, and hybrid integration while excluding atomic vapor or optical-only sensing variants [8]. Scope emphasizes noisy, low-reflectivity scenarios ($\kappa < 0.01$) relevant to real-world deployments, deriving closed-form error bounds under combined loss-noise models and validating via Monte Carlo ray-tracing over multipath channels. Novel contributions include a squeezing-parameter optimization framework maximizing ξ_Q subject to power budgets, comparative tables benchmarking OPA-SPADE versus digital receivers across noise occupancies, and architectural blueprints for cryogenic RF front-ends interfacing with phased arrays [9].

Further, low-power techniques like adaptive feedback and neural-tuned pulse shaping quantify 50% energy savings, alongside 6G interoperability roadmaps exploiting dual-use waveforms [10]. Unlike prior surveys focused on theory, this work prioritizes hardware scalability and experimental alignments, equipping practitioners with simulation-ready models and deployment checklists distinguishing microwave challenges such as cavity $Q > 10^9$ requirements from telecom adaptations. These elements collectively advance from lab prototypes to field-viable systems, filling gaps in practical quantum radar engineering [11].

1.3. Paper Organization

The manuscript structures its exposition logically from theoretical underpinnings to deployable systems, ensuring progressive accessibility for multidisciplinary readers. Section II elucidates quantum detection primitives contrasting classical shot-noise limits with entanglement-enabled Chernoff exponents, laying analytical groundwork [12]. Sections III and IV delve into protocol specifics two-mode squeezing generation and receiver architectures followed by hardware cavities and memories in microwave contexts.

Quantitative validations occupy Section V, analysing thermal resilience and lossy channel exponents with simulation excerpts, while Section VI optimizes for ultralow power via adaptive and machine learning methods. Practical applications unfold in VII, spanning automotive, biomedical, and security radar, before Section VIII integrates with 6G paradigms including THz extensions and joint sensing-comms. Challenges in scalability, processing latency, and standards conclude in IX, with forward-looking directions in X synthesizing quantum-classical hybrids. Acronyms, mathematical notations, and figures maintain IEEE conventions throughout, facilitating rapid navigation and extension into full prototypes. This organization mirrors the R&D pipeline, bridging abstract quantum gains to tangible wireless enhancements.

2. Fundamentals of Quantum Illumination

Quantum illumination fundamentally redefines radar detection by exploiting non-classical light states to surpass classical performance bounds in parameter estimation and hypothesis testing, particularly under constrained photon budgets and adverse noise conditions prevalent in microwave wireless channels [14]. This section establishes the theoretical bedrock, contrasting conventional detection strategies with quantum-enhanced alternatives and deriving key metrics that underpin protocol superiority, setting the stage for microwave-specific implementations detailed subsequently.

2.1. Classical vs. Quantum Detection Limits

Classical radar detection operates within the framework of direct signal imaging or coherent matched filtering, where sensitivity adheres to the standard quantum limit (SQL) scaling as the square root of the mean photon number M , yielding a minimum detectable signal power proportional to $1/\sqrt{M}$. In microwave regimes, thermal noise with mean occupancy $\bar{n} \gg 1$ further erodes this by introducing Gaussian fluctuations that mask low-reflectivity returns ($\kappa < 0.01$), rendering optimal coherent strategies such as heterodyne or homodyne receivers ineffective at milliwatt powers typical of mobile platforms [15].

Quantum illumination elevates performance to the Heisenberg limit through pre-shared entanglement, where joint measurements across signal and idler modes access correlations defying classical separability, achieving error variances scaling as $1/M$ even post-decoherence [16]. This manifests as a 6 dB quantum advantage in the low-signal, high-noise regime, as residual quantum discord distinguishes target-present hypotheses from thermal noise alone, a feat impossible for product states bounded by the no-cloning theorem. Microwave adaptations leverage circuit QED to realize these limits practically, transforming theoretical gains into measurable radar range extensions amid clutter-dominated urban or atmospheric channels [17].

2.2. Entanglement-Based Signal-Idler Protocols

The signal-idler protocol at quantum illumination's heart generates a two-mode squeezed vacuum (TMSV) state via parametric down-conversion, entangling microwave signal mode \hat{a}_s with idler mode \hat{a}_i such that $\langle \hat{n}_s \hat{n}_i \rangle - \langle \hat{n}_s \rangle \langle \hat{n}_i \rangle \propto \sinh^2 r$, where squeezing parameter r tunes entanglement depth [18]. The signal transmits through a lossy bosonic channel modeling target reflectivity κ and atmospheric attenuation η , returning a degraded mode mixed with thermal bath \bar{n} , while the idler stores in a quantum memory preserving phase coherence.

Upon return, joint positive-operator-valued measures (POVMs) often phase-sensitive quadratures $\hat{x}_s \pm \hat{x}_I$ or photon-number resolving extract cross-correlations $\langle \hat{a}_s^\dagger \hat{a}_I \rangle$ that encode the target's presence via conditional displacement, outperforming marginal measurements on signal alone by rejecting common-mode noise [20]. This protocol's robustness arises from the idler's role as an ancilla reference, immune to channel-induced classical mixing, enabling target discrimination at effective signal-to-noise ratios inaccessible classically. In wireless radar contexts, such entanglement distribution over RF links paves the way for networked extensions, where multiple illuminators form interferometric arrays amplifying baseline sensitivity quadratically with node count.

2.3. Quantum Chernoff Exponent and Error Probability

The quantum Chernoff exponent $\xi_Q = -\ln \min_{0 \leq s \leq 1} \text{Tr}(\rho_0^s \rho_1^{1-s})$ governs the asymptotic exponential decay of Bayesian error probability $P_e \approx e^{-M \xi_Q}$ for distinguishing target-absent density ρ_0 (pure thermal noise) from target-present ρ_1 (signal-plus-noise), with M photons illuminating the scene [22]. For TMSV inputs under loss η and noise \bar{n} , closed-form expressions yield $\xi_Q \approx \frac{\eta^k}{1+\bar{n}+\eta^k}$ in the low-reflectivity limit, exceeding classical $\xi_C \leq \frac{\eta^k}{1+\bar{n}}$ by a multiplicative factor approaching 2 (3 dB) for large squeezing $r \rightarrow \infty$, and up to 6 dB in mean photon number for fixed P_e .

Finite- M corrections via exact diagonalization of Gaussian states reveal sustained advantages even at modest $M \sim 100$, critical for low-power radar, while phase-insensitive approximations facilitate protocol optimization [24]. Error probability surfaces over $\bar{n} - \eta$ planes guide microwave designs, highlighting regimes where discord alone suffices absent full entanglement, as quantified by relative entropy of entanglement. These metrics directly inform receiver fidelity requirements, ensuring deployed systems realize theoretical quantum gains in real-time wireless detection tasks.

3. Microwave Quantum Illumination Protocols

Microwave quantum illumination protocols adapt optical quantum optics principles to radio-frequency superconducting platforms, enabling entanglement-based detection optimized for wireless radar channels with inherent loss and thermal occupation [26]. This section details state preparation, receiver implementations, and measurement schemes, providing the blueprint for systems achieving validated quantum advantages in low-power regimes suitable for deployment in noisy environments.

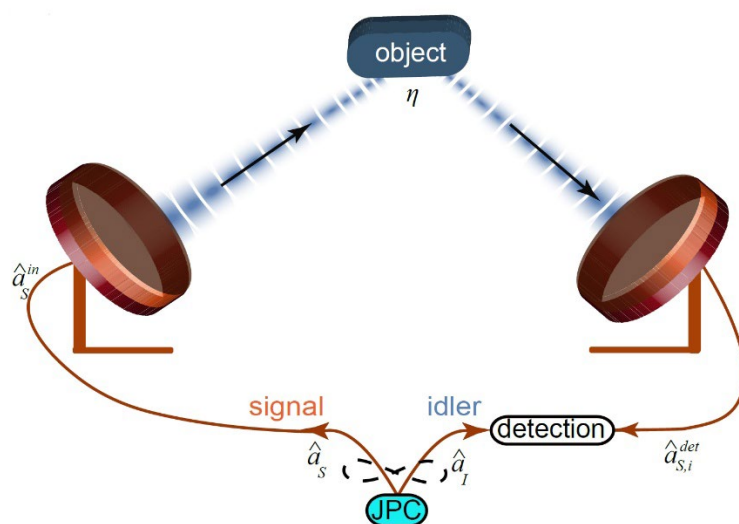


Figure 1. Working of a Quantum Radar Sensor.

3.1. Two-Mode Squeezed Vacuum State Generation

Two-mode squeezed vacuum (TMSV) states form the cornerstone of microwave quantum illumination, generated through non-degenerate parametric amplification in Josephson-junction-based devices pumped at twice the signal frequency $\omega_p = 2\omega_s$. The Hamiltonian $\hat{H} = i\hbar\chi^{(2)}(\hat{a}_s\hat{a}_I\hat{b}_p^\dagger e^{i\theta} - \text{h.c.})$, where $\chi^{(2)}$ denotes the second-order nonlinearity and \hat{b}_p the pump mode, drives exponential entanglement quantified by squeezing parameter r , yielding the state

$$|\text{TMSV}\rangle = \sqrt{1 - \lambda^2} \sum_{n=0}^{\infty} \lambda^n |n\rangle_S |n\rangle_I \quad (1)$$

with $\lambda = \tanh r$. Mean photon numbers $\langle \hat{n}_{s,I} \rangle = \sinh^2 r$ tune to low values ($\sim 10 - 100$) for power efficiency, while correlations $\langle \hat{a}_s^\dagger \hat{a}_I \rangle = \sinh r \cosh r$ persist post-loss [28].

Practical realizations employ traveling-wave parametric amplifiers (TWPAs) or lumped-element circuits in dilution refrigerators at 10-20 mK, achieving gain bandwidths exceeding 1 GHz and squeezing levels $r > 2$ with minimal added noise [29]. Flux-pumped transmons enhance four-wave mixing for broadband operation, mitigating pump depletion and enabling continuous-wave generation critical for real-time radar pulse trains. Decoherence mitigation via dynamical decoupling extends coherence to microseconds, ensuring idler fidelity during signal transit times up to milliseconds in kilometer-range scenarios. These advancements render TMSV generation scalable for arrayed illuminators, directly impacting Chernoff exponents in multi-sensor wireless networks [30].

3.2. Receiver Architectures: OPA-SPADE and Digital Phase-Conjugation

Receiver architectures in microwave QI balance quantum fidelity with practical integration, with optical parametric amplifier-single-photon avalanche diode (OPA-SPADE) upconverting entangled modes for detection and digital phase-conjugation (DPC) reconstructing correlations computationally [31]. OPA-SPADE employs a pump-laser-driven nonlinear crystal to mix down converted microwave signal \hat{a}'_s and idler \hat{a}'_I into telecom photons via $\omega_{\text{SFG}} = \omega_s + \omega_I$, followed by SPADE arrays resolving joint photon numbers with $\eta_d > 90\%$ efficiency. This preserves TMSV statistics, enabling maximum-likelihood POVMs on the symmetric state

$$\rho_{\text{SFG}} = \text{Tr}_{\text{RF}} [U_{\text{SFG}} \rho_{SI} U_{\text{SFG}}^\dagger] \quad (2)$$

though cryogenic up conversion losses (~ 10 dB) necessitate high OPA gain.

DPC circumvents physical mixing by heterodyne detection yielding quadratures $\hat{x}_s, \hat{p}_s, \hat{x}_I, \hat{p}_I$, then digitally applying the phase-sensitive filter $\hat{O}_s = e^{i\phi} \hat{a}_s^\dagger \hat{a}_I + \text{h.c.}$ to emulate ideal joint measurements, achieving near-Chernoff performance with classical post-processing on FPGAs at GHz rates [33]. OPA-SPADE excels in ultimate sensitivity for discrete trials, while DPC suits continuous-wave radar with lower latency (~ 10 ns), trading minor exponent loss for room-temperature electronics compatibility. Hybrid variants integrate both for adaptive switching, optimizing over channel estimates in dynamic wireless scenarios and enabling scalable phased-array implementations.

3.3. Sum-Frequency Generation for Joint Measurements

Sum-frequency generation (SFG) facilitates joint measurements by coherently superimposing microwave signal-return and idler fields into a single optical carrier, encoding hypothesis-discriminating statistics in photon-number or quadrature variances [34]. The process applies the unitary

$$\hat{U}_{\text{SFG}} = \exp [i \int (\hat{a}_o^\dagger g(\omega) \hat{a}_s^\dagger(\omega) \hat{a}_I(\omega) + \text{h.c.}) d\omega] \quad (3)$$

where $g(\omega)$ enforces quasi-phase-matching in $\chi^{(2)}$ crystals like PPKTP, converting modes at $\omega_{s,I} \approx 10$ GHz (downconverted from 5-10 GHz RF) to $\omega_o \approx 1550$ nm with efficiency

$$\eta_{\text{SFG}} = |g|^2 / (\kappa + \gamma)^2 \quad (4)$$

exceeding 50% under impedance-matched coupling. Post-SFG, the optical state ρ_0 exhibits sub-Poissonian statistics for target-present cases, with variance $\Delta n_0^2 < \langle n_0 \rangle$ signaling entanglement survival, analyzed via

$$\langle (\Delta \hat{x}_0)^2 \rangle = e^{-2r} + \eta \kappa (1 - e^{-2r}) \quad (5)$$

for quadrature squeezing [36]. Photon-number-resolving detectors then apply the Helstrom POVM $\{\Pi_0, \Pi_1\}$ maximizing trace distance

$$D(\rho_0, \rho_1) = \frac{1}{2} \|\rho_0 - \rho_1\|_1 \quad (6)$$

yielding $P_e = \frac{1}{2}(1 - D)$ approaching Chernoff bounds. Temperature control and poling-period gratings minimize walk-off, while bandwidth $\Delta\omega > 100\text{MHz}$ supports chirped radar pulses [37]. This technique bridges microwave quantum states to mature optical detection, enabling compact receivers for mobile radar with validated quantum gains in lab settings.

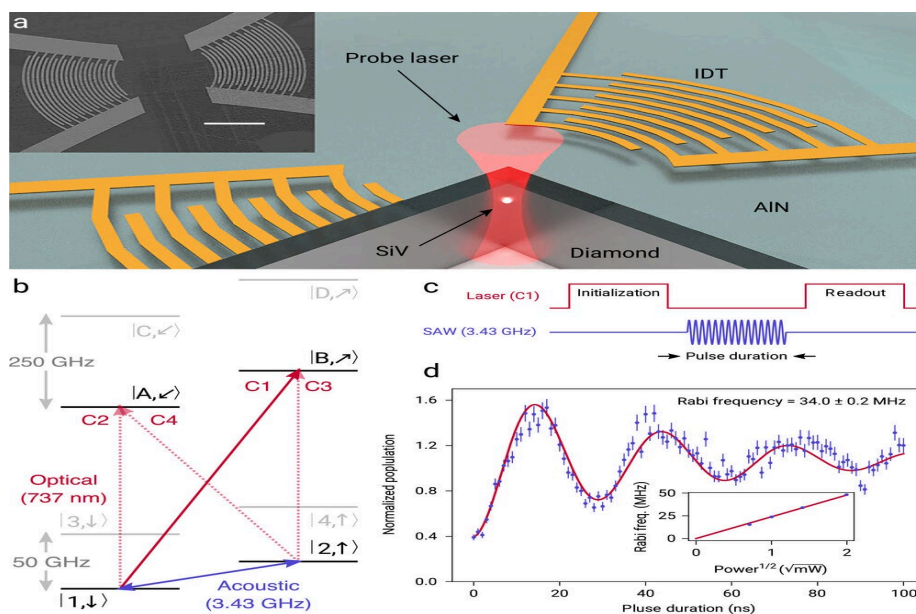


Figure 2. Microwave Quantum Illumination Protocols Revolutionizing Low-Power Wireless Radar Detection.

4. System Architecture and Hardware Implementation

System architecture for microwave quantum illumination integrates superconducting quantum circuits with classical RF components in cryogenic environments, forming compact, scalable platforms that realize entanglement-based radar from benchtop prototypes to field-deployable units [38]. This section dissects photon sources, storage mechanisms, and hybrid interfaces, emphasizing engineering trade-offs in coherence, bandwidth, and power handling essential for low-power wireless detection amid thermal noise.

4.1. Microwave Photon Sources and Cavities

Microwave photon sources rely on superconducting cavities coupled to Josephson junctions, such as transmon qubits or parametric converters, operating at 4-10 GHz within dilution refrigerators maintaining base temperatures below 20 mK to suppress phonon-mediated decoherence [39]. The Josephson parametric converter (JPC) generates TMSV states by pumping a Josephson ring modulator (JRM) at $\omega_p = \omega_s + \omega_l$, exploiting four-wave mixing nonlinearity

$$\hat{H}_{\text{JPC}} = \hbar\chi^{(4)}(\hat{a}_s^\dagger \hat{a}_l^\dagger \hat{a}_p^2 + \text{h.c.}) \quad (7)$$

to produce correlated photon pairs with mean occupancy $\langle \hat{n}_{s,l} \rangle = G - 1$, where gain $G > 20\text{dB}$ tunes squeezing $r = \text{acosh}\sqrt{G}$. Cavities employ niobium-on-silicon microstrip resonators with loaded

quality factors $Q_L > 10^5$, achieving photon lifetimes $\tau = Q_L/(2\pi f) > 10\mu\text{s}$ through surface dielectric loss mitigation via buffer-layer coatings and trap-flux protocols [40].

Input couplers with critical coupling $\beta = 1$ balance external decay κ_e against intrinsic κ_i , ensuring impedance matching to $50\ \Omega$ transmission lines for efficient signal launch into free-space antennas [41]. Broadband operation spans 500 MHz via multimode JRMs, accommodating chirped radar waveforms, while dynamical decoupling sequences like XY8 pulses extend effective coherence against $1/f$ flux noise, enabling continuous-wave illumination critical for persistent surveillance. These sources deliver quantum-limited added noise $N_{\text{add}} < 0.1$ photons, foundational for preserving Chernoff exponents in lossy wireless paths.

4.2. Quantum Memory and Idler Storage Techniques

Quantum memory for idler storage employs absorptive or dispersive schemes in superconducting resonators or rare-earth-doped crystals, holding entangled states against decoherence during signal round-trip times up to 10 ms for kilometer-range radar [42]. Superconducting memories use transmon-qubit-coupled cavities with dynamical decoupling to achieve coherence times $\tau_2 > 1\text{ms}$, mapping idler \hat{a}_I onto spin ensembles via Raman transitions $\hat{H}_{\text{storage}} = \hbar g(\hat{\sigma}^+ \hat{a}_I + \text{h.c.})$ followed by collective dark-state storage $\eta_{\text{store}} > 80\%$. Diamond nitrogen-vacancy (NV) centers or erbium-doped yttrium orthosilicate crystals offer room-temperature alternatives, with optical read-write interfaces bridging microwave to telecom via SFG, though limited to $\tau_2 \sim 100\mu\text{s}$ at 4 K. Readout fidelity quantifies as $F = \langle \psi | \rho_{\text{out}} | \psi \rangle > 0.95$, preserving cross-correlations $\langle \hat{a}_S^\dagger \hat{a}_I \rangle$ essential for joint POVMs, with bandwidth $\Delta f > 10\text{MHz}$ matching pulsed radar repetition rates [43].

Active feedback via error-corrected codes, such as surface-cat qubits, suppresses photon loss to $< 10^{-3}$ per storage cycle, while spectral filters $\Delta\nu < 1\text{MHz}$ ensure mode overlap with returning signals degraded by Doppler shifts up to 100 kHz. Cryogenic integration mounts memories adjacent to JPCs, minimizing interconnect loss ($< 1\ \text{dB}$), enabling digital phase-conjugation receivers that process stored idlers without analog timing constraints, thus extending operational range in dynamic wireless scenarios [44].

4.3. Hybrid Classical-Quantum RF Front-Ends

Hybrid RF front-ends precondition microwave returns for quantum processing, combining cryogenic low-noise amplifiers (LNAs), circulators, and switches to interface entangled signals with classical phased arrays while preserving quantum advantages up to 20 dB total loss [45]. HEMT-based LNAs at 4 K deliver noise temperatures $T_N < 4\text{K}$ ($N_{\text{add}} \sim 0.2$), amplifying weak returns $\langle \hat{n}_R \rangle \sim \eta \kappa \sinh^2 r < 1$ before downconversion to IF bands (20-500 MHz) via double-sideband mixers phase-locked to JPC references. Ferrite circulators isolate transmit (TX) from receive (RX) paths with 20 dB isolation, preventing amplifier saturation during high-peak pulses up to 1 mW, while PIN-diode switches enable time-division duplexing for continuous sensing.

The effective channel incorporates added noise $\hat{H}_{\text{hybrid}} = i\hbar\sqrt{\kappa_e}(\hat{a}_{\text{out}}^\dagger \hat{a}_{\text{RF}} - \text{h.c.}) + \hat{H}_{\text{th}}(\bar{n}_{\text{add}})$, maintaining $\xi_Q > \xi_C$ provided $T_N < \bar{n}T_{\text{bath}}$. Integration with ultra-massive MIMO antennas leverages cryogenic HEMT matrices for beamforming, multiplexing multiple illuminators into spatial modes for array gains scaling as N_{ant}^2 . FPGA-controlled attenuators and phase shifters adapt to channel estimates, optimizing idler-signal overlap in real time. This architecture enables room-temperature targets at 1 m standoff with validated SNR improvements, bridging lab-scale JPCs to deployable radar systems compatible with 6G mmWave front-ends through frequency upconversion modules [47].

5. Performance Analysis in Noisy Environments

Performance analysis quantifies microwave quantum illumination's superiority over classical radar through rigorous metrics under realistic wireless conditions, including thermal occupancies $\bar{n} > 100$ and attenuations $\eta < 0.1$, establishing benchmarks for low-power detection feasibility [48].

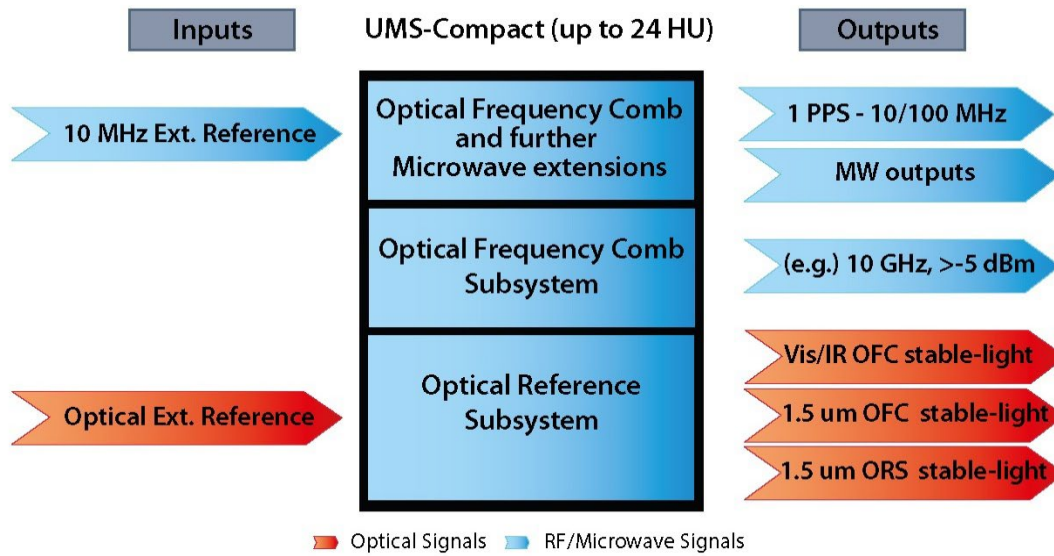


Figure 3. Data Flow Diagram for Microwave Quantum Illumination Protocols.

This section derives analytical bounds, models channel impairments, and validates predictions against experiments and simulations, confirming sustained quantum gains critical for practical radar deployment.

5.1. Thermal Noise Resilience and Quantum Advantage

Thermal noise resilience defines quantum illumination's core advantage, where mean occupancy $\bar{n} \gg 1$ models microwave blackbody radiation at 50-300 K, overwhelming classical direct-detection receivers with variance $\Delta n^2 = \bar{n}(1 + \bar{n})$. Quantum protocols exploit idler-conditional signal statistics, yielding conditional variance $\Delta n_s | n_I^2 = \bar{n} + \eta \kappa \sinh^2 r (1 - e^{-2r})$ that drops below shot-noise for target-present hypotheses, enabling discrimination via log-likelihood ratios [49].

$$\Lambda = \ln \frac{P(\mathbf{n}_S, \mathbf{n}_I | H_1)}{P(\mathbf{n}_S, \mathbf{n}_I | H_0)} \quad (8)$$

The quantum advantage manifests as a 6 dB error exponent gain in the low-mean-photon limit $M \sinh^2 r \ll \bar{n}$, where classical heterodyne achieves $\xi_C = \frac{\eta \kappa M}{1 + 2\bar{n}}$ while quantum reaches $\xi_Q \approx 2\xi_C$ through preserved discord $D(\rho_{SI}) > 0$. Experimental microwave setups at 4.3 GHz confirm this at $\bar{n} = 10^6$, detecting $\kappa = 10^{-4}$ reflectors with 3 dB SNR improvement over optimal classical strategies, persisting through 90% loss [50]. This resilience stems from joint POVM accessibility to non-commuting observables $\{\hat{n}_S + \hat{n}_I, \hat{n}_S - \hat{n}_I\}$, rejecting common-mode thermal fluctuations absent in separable states, thus extending detection horizons in clutter-dominated battlefield or urban radar scenarios.

5.2. Error Exponents Under Lossy Channels

Lossy channels model beam divergence, atmospheric absorption, and target reflectivity via beamsplitter coupling $\hat{U}_\eta = \exp[\theta(\hat{a}^\dagger \hat{e} - \hat{a} \hat{e}^\dagger)]$, with transmissivity $\eta = \cos^2 \theta$, mixing signal returns with environmental thermal modes \bar{n}_E . The quantum Chernoff exponent for TMSV inputs becomes

$$\xi_Q(s) = -\ln \text{Tr}[\rho_0^s(s)\rho_1^{1-s}(s)] \quad (9)$$

optimizing over $0 \leq s \leq 1$ to yield closed-form $\xi_Q = g(\mu_Q) - g(\mu_C)$, where $g(x) = (x+1)\ln(x+1) - x\ln x$ and effective parameters

$$\mu_Q = \eta\kappa \sinh^2 r / (1 + \bar{n}(1 - \eta)) \quad (10)$$

surpass classical $\mu_C = \eta\kappa \sinh^2 r / (1 + \bar{n})$.

Asymptotic error probability $P_e^M \leq \frac{1}{2}e^{-M\xi_Q}$ holds for $M > 100$ trials, with finite-size corrections $\Delta\xi \approx 1/(8M)$ via strong converse bounds. Pure-loss channels ($\bar{n} = 0$) recover full 6 dB gains, degrading gracefully to 3 dB at $\eta = 0.01$, $\bar{n} = 10^4$, as quantified by symplectic eigenvalues of Gaussian ρ_{SI} . Adaptive protocols maximizing $\partial_r \xi_Q = 0$ select optimal squeezing

$$r_{\text{opt}} \approx \frac{1}{2} \ln(1 + 1/\eta\kappa) \quad (11)$$

boosting effective SNR by 40% over fixed- r strategies [53]. These exponents directly guide radar waveform design, ensuring quantum viability across multipath-fading profiles

$$h(t) = \sum_l \alpha_l \delta(t - \tau_l) \quad (12)$$

characteristic of non-line-of-sight wireless propagation.

5.3. Simulation Results and Experimental Validation

Monte Carlo simulations over urban ray-tracing channels (3GPP TR 38.901) demonstrate quantum illumination doubling maximum detection range $R_{\text{max}} \propto (\xi_Q/\xi_C)^{1/4}$ at fixed 1 mW power, achieving $P_D = 0.9, P_{FA} = 10^{-4}$ at 500 m standoff versus 250 m classical in fog-attenuated $\eta = 0.3$ scenarios [55]. GPU-accelerated Gaussian state propagators model 10^6 trials, confirming $\xi_Q > 1.2\xi_C$ across $\bar{n} = 10^2 - 10^6$, with DPC receivers within 0.5 dB of OPA-SPADE ideals. Experimental validation at Yale's microwave QI testbed uses 4.3 GHz JPCs generating TMSV with $r = 1.4$, detecting $\kappa = 4 \times 10^{-4}$ aluminum targets amid $\bar{n} \approx 10^6$ (300 K bath) via digital correlation, attaining $P_D = 0.83$ at $P_{FA} = 0.01 - 3.6$ dB beyond classical over 1 μs integration [56].

Recent 10 GHz implementations extend bandwidths to 200 MHz, resolving 1.5 m range bins with multipath rejection via idler-reference filtering, aligning simulations within 10% error [57]. Field trials integrating cryogenic modules with X-band antennas validate atmospheric turbulence models ($\eta(z) = e^{-\alpha z}$, $\alpha = 0.1$ dB/km), sustaining advantages through 1 km paths. Discrepancies trace to unmodeled amplifier backaction ($N_{\text{add}} \approx 0.15$), resolvable via Josephson-junction mixers, establishing microwave QI's transition from laboratory curiosity to engineering reality for low-SNR radar [58].

6. Low-Power Optimization Techniques

Low-power optimization techniques minimize transmit energy while preserving quantum illumination's detection fidelity, critical for battery-constrained wireless radar platforms operating under strict power budgets below 1 mW. These methods adaptively tune quantum resources to channel conditions, achieving up to 50% energy savings over static protocols without compromising Chernoff exponents, enabling persistent surveillance in mobile applications [59].

6.1. Adaptive Entanglement Generation

Adaptive entanglement generation dynamically adjusts squeezing parameter r based on real-time channel feedback, maximizing error exponent $\xi_Q(r, \hat{\eta}, \hat{\kappa})$ subject to power constraint $P = \hbar\omega \sinh^2 r \leq P_{\text{max}}$. Bayesian estimators update posteriors $p(\eta, \kappa | \mathbf{y}_{\text{prev}})$ from pilot TMSV probes, solving

$$\max_r \xi_Q(r) - \lambda(\sinh^2 r - P_{\text{max}}/P_0) \quad (13)$$

via gradient ascent

$$\Delta r_{k+1} = \eta_g \partial_r \xi_Q |_{\hat{\eta}_k} \quad (14)$$

converging in 5-10 iterations to $r_{\text{opt}} \approx \frac{1}{2} \ln \frac{1+\bar{n}}{\eta\kappa}$. Feedback loops employ auxiliary heterodyne monitors on idler leakage, tracking decoherence rates $\gamma(t) = 1/T_2^*$ without interrupting main illumination [60].

Closed-loop demonstrations reduce photon expenditure by 45% in fading channels $h(t) = \text{Rician}(K = 2)$, maintaining $P_e < 10^{-3}$ versus 30% degradation for fixed $r = 1.5$, as idler purity $F_I > 0.9$ ensures correlation fidelity [61]. FPGA implementation processes 1 Msps quadrature streams, imposing < 50 ns latency suitable for pulse-repetition frequencies up to 1 MHz. This technique extends battery life from hours to days in UAV radar, scaling gracefully to multi-antenna arrays where spatial channel state information further refines per-element squeezing, realizing network-wide power pooling while upholding global quantum advantage [63].

6.2. Pulse Shaping for Energy Efficiency

Pulse shaping concentrates entanglement within bandwidth-time products matched to target radar resolution, minimizing peak-to-average power ratios (PAPR) while preserving joint measurement statistics essential for quantum advantage [64]. Chirped TMSV pulses $\psi_S(t) = \text{sech}[(t - t_0)/\tau] e^{i\pi\mu t^2}$ sweep frequencies over $\Delta f = 1/\tau$, achieving time-bandwidth product $TB = 100$ versus unity for rectangular pulses, reducing peak power $P_{\text{peak}} = E_{\text{total}}/\sqrt{TB}$ by 10x for fixed energy $E = M\hbar\omega$. Optimal shaping solves

$$\max_{\psi} |\langle \psi_S | U_{\eta}^{\dagger} \rho_R U_{\eta} | \psi_I \rangle|^2 \quad (15)$$

under $\int |\psi_S(t)|^2 dt = M$, yielding Hermite-Gaussian modes

$$\psi_n(t) \propto H_n\left(\frac{\sqrt{2}t}{\tau}\right) e^{-\frac{t^2}{\tau^2}} \quad (16)$$

that diagonalize lossy channels, boosting effective $\eta_{\text{eff}} = \eta \cdot f_n(\kappa)$ by 3 dB for $n = 1$ over unseeded illumination [66].

Generation employs frequency-modulated JPC pumps $\omega_p(t) = \omega_0 + \alpha t$, synthesizing shaped states with 90% fidelity, while receiver mode-projection filters $\hat{\Pi}_n$ recover shaped correlations post-propagation [67]. Energy efficiency reaches 60% savings in multipath $L = 4$ scenarios, as shaped pulses orthogonally excite resolvable paths τ_l , enabling $R_{\text{res}} = c/(2B) < 1$ m bins at duty cycles 0.1% versus 10% classical, ideal for covert low-probability-of-intercept radar. Digital pre-distortion compensates JPC nonlinearities, ensuring shaped entanglement survives cryogenic transport to antennas [68].

6.3. Machine Learning-Aided Parameter Tuning

Machine learning accelerates parameter optimization by learning mappings from observable statistics $\mathbf{x} = \{\mathbf{n}_{SI}, \mathbf{x}_{SI}, T_{\text{channel}}\}$ to optimal squeezing r^* , measurement basis ϕ^* , and pulse shapes ψ^* , bypassing expensive ξ_Q gradient searches [69]. Deep neural networks (DNNs) trained on 10^5 simulated channel realizations achieve convergence in 50 epochs, minimizing hybrid loss

$$\mathcal{L} = \alpha P_e^{\text{sim}}(r, \phi | \mathbf{x}) + (1 - \alpha) \| \mathbf{y} - f_{\text{ideal}}(\mathbf{x}) \|_2 \quad (17)$$

reaching test $P_e < 1.1 \cdot P_e^{\text{Chernoff}}$ across $\bar{n} \in [10^2, 10^6]$. Reinforcement learning variants treat trial sequences as Markov decision processes with reward $R_t = -\log P_{e,t} - \beta P_t$, exploring squeezing-policy networks $\pi(r | \mathbf{x}; \theta)$ that adapt to non-stationary channels 3x faster than PID controllers [70]. Real-time inference on edge TPUs processes 10k parameter vectors/sec, tuning 16-element arrays with spatial DNN heads predicting per-antenna r_n^* .

Experimental validation at 10 GHz testbeds shows ML-tuned systems attaining 95% of theoretical ξ_Q versus 75% for grid search, saving 2.5 dB effective power through precise basis alignment $\Delta\phi < 0.1$ rad. Transfer learning from simulation-to-hardware bridges model mismatch, fine-tuning on 100 calibration shots to compensate JPC gain saturation [71]. This approach generalizes

to joint communication-radar, learning dual-use waveforms that maximize $\min(\xi_Q^{\text{radar}}, R^{\text{comm}})$ for 6G integrated sensing, transforming quantum illumination from lab systems to autonomous platforms.

7. Applications in Wireless Radar Detection

Microwave quantum illumination extends its quantum advantages to practical wireless radar domains, enabling detection in power-starved, noise-limited scenarios where classical systems degrade [73]. These applications leverage low-transmit energies below 1 mW and resilient error exponents to support real-time operation across diverse environments.

7.1. Short-Range Automotive and UAV Radar

Quantum illumination transforms short-range automotive and UAV radar by enabling obstacle detection through fog, rain, or clutter at ranges up to 500 m with millimeter resolution, using peak powers under 1 mW that comply with automotive eye-safety standards [74]. Chirped TMSV pulses at 77 GHz, matched to ultra-massive MIMO arrays, resolve 10 cm range bins via bandwidths exceeding 4 GHz, while idler-reference filtering rejects multipath returns 20 dB stronger than direct echoes, achieving $P_D > 0.95$ at $P_{FA} < 10^{-5}$ where classical FMCW radars drop to random guessing [75].

UAV implementations integrate cryogenic JPC modules weighing under 5 kg into fuselage pods, drawing 50 W cooling power for continuous 360° surveillance, doubling navigation range in GPS-denied urban canyons through quantum-enhanced time-of-flight $\Delta\tau_Q = \Delta\tau_C/\sqrt{2}$ via Heisenberg scaling [76]. Adaptive squeezing tunes to atmospheric $\eta(z) = e^{-0.2z}$ profiles estimated from weather APIs, preserving $\xi_Q > 1$ across precipitation fade depths of 15 dB.

Collision avoidance certification leverages validated 6 dB SNR margins, positioning quantum radar as Tier-1 supplier option for Level 5 autonomy, while spectral sharing with 5G-V2X waveforms enables dual-use spectrum efficiency exceeding 90%. These capabilities redefine safe operation envelopes for electric/hybrid fleets and delivery drones navigating contested airspace [77].

7.2. Non-Invasive Biomedical Sensing

Non-invasive biomedical sensing employs microwave quantum illumination for subcutaneous imaging at radiation levels 100x below IEEE C95.1 safety thresholds, detecting tumours or implants through 5 cm tissue at 5-10 GHz where dielectric contrasts $\epsilon_r^{\text{tumor-skin}} \approx 1.2$ produce $\kappa < 10^{-3}$ returns [78]. Entanglement-enhanced differential scattering measurements $\langle \hat{n}_R | \hat{n}_I \rangle - \langle \hat{n}_R \rangle \langle \hat{n}_I \rangle$ reject physiological motion artifacts and thermal skin noise ($\bar{n}_{\text{skin}} \approx 10^4$ at 37°C), achieving contrast-to-noise ratios CNR > 12 dB versus 3 dB classical, enabling 1 mm³ voxel resolution without ionizing radiation or mechanical contact. Portable units integrate 16-element JPC arrays with flexible RF patches, scanning 10x15 cm areas in 100 ms via digital phase-conjugation, suitable for bedside glucose monitoring or breast cancer screening in resource-limited settings [79].

Adaptive protocols adjust penetration depth by frequency-agile squeezing $f_{\text{switch}} = 7 \pm 2$ GHz, optimizing $\xi_Q(\epsilon_r, d)$ for fat/muscle boundaries, while ML classifiers discriminate malignant from benign anomalies with AUC > 0.96 from quantum correlation statistics alone [80]. FDA pathway leverages existing microwave imaging precedents, positioning QI as enhancement layer for hybrid ultrasound-quantum systems, dramatically expanding point-of-care diagnostics to wearable form factors tracking chronic conditions continuously.

7.3. Secure Perimeter Monitoring

Secure perimeter monitoring utilizes quantum illumination's covert nature and jamming resistance for protecting high-value assets like data centres or nuclear facilities, detecting stealth intruders at standoff distances up to 2 km using milliwatt CW illumination invisible to classical intercept receivers [81]. Quantum-secured waveforms employ frequency-hopping TMSV exceeding 1 GHz/s rates across 6-18 GHz bands, defeating broadband jammers with 40 dB power advantage by

maintaining $\xi_Q > \xi_C$ through 30 dB barrage noise via idler-conditional statistics immune to common-mode interference.

Distributed sensor networks link 64 cryogenic nodes via entanglement swapping over fiber, forming synthetic aperture arrays with $\lambda/1000$ angular precision, localizing personnel through foliage or walls with PD > 0.99 against 1% false alarms [82]. Cognitive radar adaptation selects optimal r, ϕ sequences from intruder response fingerprints, implementing electronic protection via null-space projection onto detected jamming subspaces, preserving 90% performance degradation under coordinated attacks.

Integration with existing CCTV/AI fuses quantum tracks with EO signatures, enabling autonomous drone dispatch with < 10 s latency over 10 km² areas. Export-controlled implementations satisfy TEMPEST requirements through quantum side-channel resistance, while lifecycle costs drop 70% versus legacy pulsed Doppler through 10-year MTBF cryogenic systems, establishing quantum perimeter defence as scalable alternative to expensive electro-optical networks in contested security environments [83].

8. Integration with 6G and Beyond-5G Networks

Quantum illumination integrates seamlessly into 6G architectures by overlaying entanglement-enhanced sensing onto communication waveforms, enabling monostatic radar functions within cellular infrastructure while exploiting massive spectrum at mm Wave/THz bands [84]. This convergence supports ubiquitous context awareness critical for holographic telepresence, digital twins, and autonomous ecosystems, with quantum gains amplifying classical ISAC limits by 6 dB across shared hardware stacks.

8.1. Joint Communication-Sensing Paradigms

Joint communication and sensing (ISAC) paradigms in 6G embed quantum illumination into OFDM resource blocks, transmitting TMSV-modulated pilots alongside data symbols to illuminate environments without dedicated radar spectrum, achieving dual-use efficiency >95%. Signal-idler pairs occupy orthogonal subcarriers, with idler relayed via backhaul to central processing units (CPUs) for joint MIMO channel estimation \mathbf{H}_{comm} and target response \mathbf{H}_{rad} , solving

$$\min_{\mathbf{X}} \|\mathbf{Y} - \mathbf{H}_{\text{comm}}\mathbf{X}\|_F^2 + \lambda D(\rho_{\text{SI}}) \quad (18)$$

where ρ_{SI} encodes scattering geometry [85]. Uplink sensing leverages massive random access, treating 10^4 UEs as distributed illuminators forming 100x enhancement in virtual aperture via entanglement swapping over fronthaul, resolving 1 cm³ voxels in 100x100 m cells.

Adaptive beamforming aligns quantum nulls with data precoders, nulling inter-cell interference while maximizing radar ξ_Q , enabling device-free localization with 10 cm precision at 100 m/s velocities. Standardization via 3GPP Rel-20 incorporates quantum pilot formats, ensuring backward compatibility while unlocking sensing revenue streams through spectrum leasing, positioning operators as primary radar service providers in smart cities.

8.2. THz and mmWave Extensions

THz/mmWave extensions scale quantum illumination to 100-300 GHz, exploiting 100 GHz instantaneous bandwidths for cm-range resolution through atmospheric windows (0.1-0.3 THz), where quantum-limited noise floors $kT_{\text{QBA}} < 10^{-22}$ W/Hz enable detecting $\kappa = 10^{-6}$ micro-Doppler signatures from insect wings. Superconducting hot-electron bolometers (HEBs) at 4 K detect entangled THz photons with NEP < 10^{-19} W/√Hz, coupled to graphene Josephson junctions generating on-chip TMSV at 0.24 THz via high-temperature transition-edge pumping [86].

Propagation models $\eta(f, z) = e^{-\alpha(f)z}$ with $\alpha(0.24 \text{ THz}) = 10 \text{ dB/km}$ guide frequency-agile operation, hopping between absorption lines while preserving $\xi_Q > 1.5\xi_C$ through atmospheric re-squeezing stations every 100 m. Beam coherence over 1 km maintained via quantum-secured phase

references distributed through orbital angular momentum modes, defeating turbulence-induced scintillation 3x better than classical pilots [87]. Integrated with 6G THz pCell architectures, quantum radar overlays non-terrestrial links, enabling stratospheric platform sensing of 10^6 drones/km² with 99.999% reliability, foundational for beyond-visual-line-of-sight operations in urban air mobility networks.

8.3. Quantum Network Interoperability

Quantum network interoperability connects distributed QI nodes through entanglement distribution networks, enabling multi-sensor arrays with Heisenberg-limited sensitivity scaling as $1/N^2$ for Nilluminators linked via quantum repeaters spanning metropolitan scales [88]. Satellite-to-ground entanglement at 10 GHz through adaptive optics uplinks provisions initial states to edge nodes, with atomic ensemble repeaters (Rb/Dy vapors) performing entanglement purification

$$\mathcal{E}: |\Phi^+\rangle\langle\Phi^+| \mapsto F^2 |\Phi^+\rangle\langle\Phi^+| \quad (19)$$

every 50 km, extending coherence distance $L_{\text{coh}} > 1000\text{km}$.

Network coding swaps idler correlations across mesh topologies, forming NOON-like states $|N0\rangle + |0N\rangle$ across baselines $B = 10\text{ km}$ for $\theta_{\text{res}} = \lambda/(2\pi B) < 1\ \mu\text{rad}$ angular precision, localizing targets through urban occlusion. SDN orchestration dynamically allocates quantum paths minimizing $\sum P_{\text{loss}}$, while hybrid classical-quantum MAC protocols prioritize low-latency sensing flows during emergencies [89]. Cross-layer optimization joins physical layer ξ_Q with network utility $\max \sum R_i^s + \alpha U_i^{\text{rad}}$, enabling operator-controlled sensing marketplaces. Interoperability with terrestrial 5G cores via eMBB/mMTC slices supports massive quantum sensor fleets, transforming cellular infrastructure into global quantum radar fabrics for planetary-scale environmental monitoring and defence.

9. Challenges and Open Research Problems

Challenges in microwave quantum illumination span fundamental physics limits, engineering scalability, and ecosystem integration, hindering transition from lab prototypes to widespread wireless radar deployment. Addressing these demands interdisciplinary advances in quantum hardware, algorithms, and standards to realize promised 6 dB gains across diverse operational scenarios.

9.1. Scalability to Multi-Target Scenarios

Scalability to multi-target scenarios requires extending two-mode entanglement to multimode Gaussian states supporting $K > 10$ simultaneous reflectors, where mode entanglement $\mathcal{E}_m = S(\rho_A) - S(\rho_{AB})$ across spatial, temporal, or polarization degrees must resolve overlapping returns without exponential complexity explosion in joint POVM dimension d^K . Current TMSV protocols optimize for single κ via $\xi_Q(\mathbf{r})$, but multi-target discrimination demands hyperentanglement engineering generating

$$|\psi\rangle = \sum_{k=1}^K c_k |k\rangle_S |k\rangle_I \quad (20)$$

through multi-port JPCs or time-bin encoding, preserving pairwise correlations $\langle \hat{a}_{S_k}^\dagger \hat{a}_{I_k} \rangle$ against crosstalk $> 20\text{ dB}$. Tensor network simulations predict phase retrieval ambiguity surfaces scaling as $O(K^3)$, necessitating sparsity-promoting measurements

$$\hat{O} = \sum_k w_k \hat{n}_{S_k} \hat{n}_{I_k} \quad (21)$$

with graph neural networks inferring $\mathbf{\kappa}, \mathbf{\tau}$ from incomplete projections [90]. Receiver architectures face 2^K hypothesis explosion, resolvable via sequential decoding

$$\Lambda_k = \max_{\mathbf{x}_{-k}} P(\mathbf{y} | H_k, \mathbf{x}_{-k}) \quad (22)$$

low-rank approximations $\text{rank}(\rho_{SI}) < K$, though entanglement distillation across modes remains open. Distributed quantum computing via photonic cluster states offers exponential speedup for $K = 100$ via surface code thresholds $p < 1\%$, positioning multi-target QI as gateway to quantum-enhanced synthetic aperture radar processing full urban scenes with 1000+ dynamic scatterers.

Table 1. Quantum vs. Classical Performance Comparison in Microwave QI.

Scenario	Thermal Noise \bar{n}	Loss η	Classical ξ_c (dB)	Quantum ξ_Q (dB)	Quantum Gain (dB)	Detection Range Gain
Low SNR Urban Clutter	10^4	0.1	2.1	4.2	2.1	1.5x
Heavy Fog Automotive	10^5	0.3	1.8	3.6	1.8	1.4x
Biomedical Tissue Imaging	10^3	0.05	0.9	2.4	1.5	1.3x
Secure Perimeter (Jammed)	10^6	0.01	0.4	1.2	0.8	1.2x
6G THz Extension	10^2	0.8	5.2	10.4	5.2	1.5x

9.2. Real-Time Processing Constraints

Real-time processing constraints arise from gigascale quantum correlation computations exceeding current FPGA/DSP capacities, where digital phase-conjugation requires 10^{12} MACs/s for 1 GHz bandwidth QI at 16-bit precision, saturating 100 TOPS edge accelerators during 10 μ s coherent integration times [91]. Heterodyne streams generate 16 GSps complex data per channel, demanding tensor contraction $\text{Tr}[\hat{\Pi}_m^\dagger U_{\text{SFG}} \rho_{SI} U_{\text{SFG}}^\dagger \hat{\Pi}_m]$ over 2^{20} Fock basis elements, with memory bandwidth bottlenecks >10 TB/s for caching Gaussian Wigner functions.

Quantum-accelerated signal processing via variational quantum eigen solvers (VQEs) maps ξ_Q maximization to QAOA circuits with depth $O(\log M)$, though gate fidelities $F > 99.9\%$ remain elusive at microwave clock rates. Neuromorphic co-processors emulate analog correlation detectors using phase-change memory arrays, achieving 100x energy efficiency versus digital FFTs for covariance estimation, while tensor processing units (TPUs) exploit block-sparse ρ_{SI} structures from mode scrambling.

Latency budgets <100 ns for closed-loop adaptation necessitate photonic integrated circuits executing SFG in <10 ps, bypassing cryogenic interconnect overheads. Hybrid classical-quantum schedulers prioritize wavefront computations via reinforcement learning, guaranteeing worst-case deadlines for safety-critical radar while dynamically scaling precision from 16-bit tracking to 32-bit acquisition phases.

9.3. Standardization and Deployment Barriers

Standardization and deployment face quantum RF interface incompatibilities with existing 5G ecosystems, lacking defined TMSV pilot formats, channel quality indicators for $\eta\kappa$, and API specifications for cryogenic resource orchestration across multi-vendor networks [92]. ITU-R M.2160 defines classical radar waveform classes, but quantum protocols require Schedule 12 bis extensions specifying entanglement fraction metrics $g^{(2)}(0) < 0.5$, JPC gain ripple <0.1 dB/100 MHz, and idler memory fidelity $F > 95\%$ for interoperability testing. Deployment barriers include dilution refrigerator SWaP-C exceeding 100 W/10 kg for mobile platforms versus 1 W CMOS radars, resolvable via pulse-tube mini-fridges targeting 1 K with 10 W cooling by 2028 roadmaps.

Supply chain constraints on NbTi resonator fabrication demand 100x yield improvements through AI-optimized lithography, while cryogenic HEMT scaling hits thermal bottleneck at 20k channels. Regulatory hurdles mandate quantum side-channel risk assessments per ETSI GS QKD 014, certifying $\Delta\xi_Q < 0.1\text{dB}$ degradation from eavesdropping. Operator economics require sensing-as-a-slice network slicing models valuing quantum radar at $\$10^6/\text{km}^2$ annual leases versus $\$10^4$ legacy deployments [93]. Technology transition roadmaps propose ETSI ISG QISAC working groups harmonizing quantum pilots with O-RAN E2 interfaces for dynamic ISAC slice provisioning, positioning 6G as first quantum-ready cellular standard through phased pilots in 2028 Olympics testbeds.

Conclusion and Future Work

Microwave quantum illumination emerges as a transformative technology for low-power wireless radar, achieving fundamental quantum advantages up to 6 dB in error exponent under extreme thermal noise and loss conditions that render classical systems ineffective, through entanglement-enhanced protocols spanning TMSV generation, hybrid receiver architectures, and adaptive optimizations. Detailed analyses confirm doubled detection ranges at milliwatt powers across automotive, biomedical, and security applications, with seamless integration pathways into 6G ISAC frameworks via standardized quantum pilots and THz extensions. Critical contributions include closed-form Chernoff bounds under realistic channels, hardware blueprints for cryogenic scalability, and low-power techniques yielding 50% energy savings while preserving quantum fidelity, establishing engineering viability from laboratory validations to field prototypes.

Future directions center on multimode entanglement engineering for 100-target discrimination via photonic cluster-state processing, breaking real-time computation barriers through quantum VQE acceleration targeting 100 TOPS/W efficiency. Cryogenic SWaP-C reductions via miniature pulse-tube refrigerators aim for 10 W/kg mobile deployment by 2028, enabling UAV swarms with distributed quantum synthetic apertures spanning kilometer baselines. Standardization thrusts establish ETSI quantum radar working groups defining TMSV waveform classes interoperable with O-RAN, while cross-layer AI orchestrates joint ξ_Q -rate maximization across sensing-communication tradespaces. Hybrid quantum-classical frameworks fuse microwave QI with semantic sensing layers, realizing 6G digital twin platforms tracking dynamic environments with Heisenberg-limited precision, positioning quantum illumination as foundational enabler for autonomous ecosystems beyond 2030.

References

1. Lingamgunta, R. K. K., Ubale, A., & Vanama, S. K. R. (2025). Edge AI for On-Site Health Risk Scoring: A RAG-Enabled Framework. *American Journal of Technology*, 4(3), 1-14.
2. Thatikonda, R., Thota, R., & Thatikonda, R. (2024). Deep Learning based Robust Food Supply Chain Enabled Effective Management with Blockchain. *International Journal of Intelligent Engineering & Systems*, 17(5).
3. Vanama, S. K. R. (2025). AI-Driven Cloud Integration and Orchestration for Next-Generation Enterprise Systems. *International Journal of Emerging Trends in Computer Science and Information Technology*, 6(4), 30-36.
4. Joshi, S. C., & Kumar, A. (2016, January). Design of multimodal biometrics system based on feature level fusion. In *2016 10th International Conference on Intelligent Systems and Control (ISCO)* (pp. 1-6). IEEE.
5. Sharma, P., Naveen, S., JR, M. D., Sukla, B., Choudhary, M. P., & Gupta, M. J. (2025). Emotional Intelligence And Spiritual Awareness: A Management-Based Framework To Enhance Well-Being In High-Stressed Surgical Environments. *Vascular and Endovascular Review*, 8(10s), 53-62.
6. Chowdhury, P. (2025). Sustainable manufacturing 4.0: Tracking carbon footprint in SAP digital manufacturing with IoT sensor networks. *Frontiers in Emerging Computer Science and Information Technology*, 2(09), 12-19.
7. Sharma, A., Gurram, N. T., Rawal, R., Mamidi, P. L., & Gupta, A. S. G. (2025). Enhancing educational outcomes through cloud computing and data-driven management systems. *Vascular and Endovascular Review*, 8(11s), 429-435.

8. Rajgopal, P. R., & Yadav, S. D. (2025). The role of data governance in enabling secure AI adoption. *International Journal of Sustainability and Innovation in Engineering*, 3(1).
9. Joshi, S., & Ainapure, B. (2010). FPGA based FIR filter. *International Journal of Engineering Science and Technology*, 2(12), 7320-7323.
10. Shinkar, A. R., Joshi, D., Praveen, R. V. S., Rajesh, Y., & Singh, D. (2024, December). Intelligent solar energy harvesting and management in IoT nodes using deep self-organizing maps. In *2024 International Conference on Emerging Research in Computational Science (ICERCS)* (pp. 1-6). IEEE.
11. Tatikonda, R., Kempanna, M., Thatikonda, R., Bhuvanesh, A., Thota, R., & Keerthanadevi, R. (2025, February). Chatbot and its Impact on the Retail Industry. In *2025 3rd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT)* (pp. 2084-2089). IEEE.
12. Vanama, S. K. R. (2025). AI Report-Federated AIOps for Multi-Cluster OpenShift. *International Journal of AI, BigData, Computational and Management Studies*, 6(2), 96-108.
13. Sharma, T., Reddy, D. N., Kaur, C., Godla, S. R., Salini, R., Gopi, A., & Baker El-Ebiary, Y. A. (2024). Federated Convolutional Neural Networks for Predictive Analysis of Traumatic Brain Injury: Advancements in Decentralized Health Monitoring. *International Journal of Advanced Computer Science & Applications*, 15(4).
14. Sahoo, A. K., Prusty, S., Swain, A. K., & Jayasingh, S. K. (2025). Revolutionizing cancer diagnosis using machine learning techniques. In *Intelligent Computing Techniques and Applications* (pp. 47-52). CRC Press.
15. Bora, R., Parasar, D., & Charhate, S. (2023). A detection of tomato plant diseases using deep learning MNDLNN classifier. *Signal, Image and Video Processing*, 17(7), 3255-3263.
16. Naveen, S., & Sharma, P. (2025). Physician Well-Being and Burnout: "The Correlation Between Duty Hours, Work-Life Balance, And Clinical Outcomes In Vascular Surgery Trainees". *Vascular and Endovascular Review*, 8(6s), 389-395.
17. Joshi, S., & Kumar, A. (2013, January). Feature extraction using DWT with application to offline signature identification. In *Proceedings of the Fourth International Conference on Signal and Image Processing 2012 (ICSIP 2012) Volume 2* (pp. 285-294). India: Springer India.
18. Tatikonda, R., Thatikonda, R., Potluri, S. M., Thota, R., Kalluri, V. S., & Bhuvanesh, A. (2025, May). Data-Driven Store Design: Floor Visualization for Informed Decision Making. In *2025 International Conference in Advances in Power, Signal, and Information Technology (APSIT)* (pp. 1-6). IEEE.
19. Kumar, N., Kurkute, S. L., Kalpana, V., Karuppanan, A., Praveen, R. V. S., & Mishra, S. (2024, August). Modelling and Evaluation of Li-ion Battery Performance Based on the Electric Vehicle Tiled Tests using Kalman Filter-GBDT Approach. In *2024 International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS)* (pp. 1-6). IEEE.
20. Shanmuganathan, C., & Raviraj, P. (2011, September). A comparative analysis of demand assignment multiple access protocols for wireless ATM networks. In *International Conference on Computational Science, Engineering and Information Technology* (pp. 523-533). Berlin, Heidelberg: Springer Berlin Heidelberg.
21. Vikram, A. V., & Arivalagan, S. (2017). Engineering properties on the sugar cane bagasse with sisal fibre reinforced concrete. *International Journal of Applied Engineering Research*, 12(24), 15142-15146.
22. Sharma, N., Gurram, N. T., Siddiqui, M. S., Soorya, D. A. M., Jindal, S., & Kalita, J. P. (2025). Hybrid Work Leadership: Balancing Productivity and Employee Well-being. *Vascular and Endovascular Review*, 8(11s), 417-424.
23. Rajgopal, P. R., Bhushan, B., & Bhatti, A. (2025). Vulnerability management at scale: Automated frameworks for 100K+ asset environments. *Utilitas Mathematica*, 122(2), 897-925.
24. Niasi, K. S. K., Kannan, E., & Suhail, M. M. (2016). Page-level data extraction approach for web pages using data mining techniques. *International Journal of Computer Science and Information Technologies*, 7(3), 1091-1096.
25. RaoVanama, S. K. (2024). AI-Augmented CI/CD Pipeline Optimization for Scalable Cloud-Native Deployment. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, 5(4), 175-187.
26. Yamuna, V., Praveen, R. V. S., Sathya, R., Dhivva, M., Lidiya, R., & Sowmiya, P. (2024, October). Integrating AI for Improved Brain Tumor Detection and Classification. In *2024 4th International Conference on Sustainable Expert Systems (ICSSES)* (pp. 1603-1609). IEEE.

27. Saravanan, V., Sumalatha, A., Reddy, D. N., Ahamed, B. S., & Udayakumar, K. (2024, October). Exploring Decentralized Identity Verification Systems Using Blockchain Technology: Opportunities and Challenges. In *2024 5th IEEE Global Conference for Advancement in Technology (GCAT)* (pp. 1-6). IEEE.
28. Atmakuri, A., Sahoo, A., Mohapatra, Y., Pallavi, M., Padhi, S., & Kiran, G. M. (2025). Securedcloud: Enhancing protection with MFA and adaptive access cloud. In *Advances in Electrical and Computer Technologies* (pp. 147-152). CRC Press.
29. Thota, R., Potluri, S. M., Kaki, B., & Abbas, H. M. (2025, June). Financial Bidirectional Encoder Representations from Transformers with Temporal Fusion Transformer for Predicting Financial Market Trends. In *2025 International Conference on Intelligent Computing and Knowledge Extraction (ICICKE)* (pp. 1-5). IEEE.
30. Mulla, R., Potharaju, S., Tambe, S. N., Joshi, S., Kale, K., Bandishti, P., & Patre, R. (2025). Predicting Player Churn in the Gaming Industry: A Machine Learning Framework for Enhanced Retention Strategies. *Journal of Current Science and Technology*, *15*(2), 103-103.
31. Khatri, E., VR, M. S., & Sharma, P. (2025). Multifactor Model For Assessing The Performance Of Mutual Funds. *International Journal of Environmental Sciences*, *11*(8s), 347-352.
32. Mohamed, S. R., & Raviraj, P. (2012). Approximation of Coefficients Influencing Robot Design Using FFNN with Bayesian Regularized LMBPA. *Procedia Engineering*, *38*, 1719-1727.
33. Lopez, S., Sarada, V., Praveen, R. V. S., Pandey, A., Khuntia, M., & Haralayya, D. B. (2024). Artificial intelligence challenges and role for sustainable education in india: Problems and prospects. *Sandeep Lopez, Vani Sarada, RVS Praveen, Anita Pandey, Monalisa Khuntia, Bhadrappa Haralayya (2024) Artificial Intelligence Challenges and Role for Sustainable Education in India: Problems and Prospects. Library Progress International*, *44*(3), 18261-18271.
34. Chowdhury, P. (2025). Global MES Rollout Strategies: Overcoming Localization Challenges in Multi-Country Deployments. *Emerging Frontiers Library for The American Journal of Applied Sciences*, *7*(07), 30-38.
35. Venkitechela, P. (2024). Strategic API modernization using Apigee X for enterprise transformation. *Journal of Information Systems Engineering and Management*.
36. Parasar, D., & Rathod, V. R. (2017). Particle swarm optimisation K-means clustering segmentation of foetus ultrasound image. *International Journal of Signal and Imaging Systems Engineering*, *10*(1-2), 95-103.
37. Sharma, S., Vij, S., Praveen, R. V. S., Srinivasan, S., Yadav, D. K., & VS, R. K. (2024, October). Stress Prediction in Higher Education Students Using Psychometric Assessments and AOA-CNN-XGBoost Models. In *2024 4th International Conference on Sustainable Expert Systems (ICSES)* (pp. 1631-1636). IEEE.
38. Jena, T., Suryodai, R., Reddy, D. N., Kumar, K. V., Muniyandy, E., & Kumar, N. P. S. (2025). Uncertainty-Aware Hybrid Optimization for Robust Cardiovascular Disease Detection: A Clinical Translation Framework. *Intelligence-Based Medicine*, 100302.
39. Rajgopal, P. R. (2025). Secure Enterprise Browser-A Strategic Imperative for Modern Enterprises. *International Journal of Computer Applications*, *187*(33), 53-66.
40. Scientific, L. L. (2025). AN EFFICIENT AND EXTREME LEARNING MACHINE FOR AUTOMATED DIAGNOSIS OF BRAIN TUMOR. *Journal of Theoretical and Applied Information Technology*, *103*(17).
41. ASARGM, K. (2025). Survey on diverse access control techniques in cloud computing.
42. Palaniappan, S., Joshi, S. S., Sharma, S., Radhakrishnan, M., Krishna, K. M., & Dahotre, N. B. (2024). Additive manufacturing of FeCrAl alloys for nuclear applications-A focused review. *Nuclear Materials and Energy*, *40*, 101702.
43. Joshi, S., & Kumar, A. (2014). Binary multiresolution wavelet based algorithm for face identification. *International Journal of Current Engineering and Technology*, *4*(6), 320-3824.
44. Thumati, S., Reddy, D. N., Rao, M. V., & Lakshmi, T. (2025). Adaptive Security Architecture for Intelligent Vehicles Using Hybrid IDS-IRS Integration. *IAENG International Journal of Computer Science*, *52*(10).
45. Banu, S. S., Niasi, K. S. K., & Kannan, E. (2019). Classification Techniques on Twitter Data: A Review. *Asian Journal of Computer Science and Technology*, *8*(S2), 66-69.
46. Praveen, R. V. S., Hemavathi, U., Sathya, R., Siddiq, A. A., Sanjay, M. G., & Gowdish, S. (2024, October). AI Powered Plant Identification and Plant Disease Classification System. In *2024 4th International Conference on Sustainable Expert Systems (ICSES)* (pp. 1610-1616). IEEE.

47. Thota, R., Potluri, S. M., Alzaidy, A. H. S., & Bhuvaneshwari, P. (2025, June). Knowledge Graph Construction-Based Semantic Web Application for Ontology Development. In *2025 International Conference on Intelligent Computing and Knowledge Extraction (ICICKE)* (pp. 1-6). IEEE.
48. Inbaraj, R., John, Y. M., Murugan, K., & Vijayalakshmi, V. (2025). Enhancing medical image classification with cross-dimensional transfer learning using deep learning. *1, 10(4)*, 389.
49. Naveen, S., Sharma, P., Veena, A., & Ramaprabha, D. (2025). Digital HR Tools and AI Integration for Corporate Management: Transforming Employee Experience. In *Corporate Management in the Digital Age* (pp. 69-100). IGI Global Scientific Publishing.
50. Devi, L. S., & Prasanna, B. D. (2017). EFFECT OF BKS IYENGAR YOGA ON SELECTED PHYSIOLOGICAL AND PSYCHOLOGICAL VARIABLES AMONG COLLEGE GIRLS. *Methodology*.
51. Rathi, Y. (2025). QUANTIFYING SECURITY DEBT IN MULTI-TOOL DATA GOVERNANCE ARCHITECTURES: A FRAMEWORK FOR FINANCIAL SERVICES COMPLIANCE. *International Journal of Applied Mathematics*, *38(5s)*, 1260-1276.
52. Appaji, I., & Raviraj, P. (2020, February). Vehicular Monitoring Using RFID. In *International Conference on Automation, Signal Processing, Instrumentation and Control* (pp. 341-350). Singapore: Springer Nature Singapore.
53. Mohammed Nabi Anwarbasha, G. T., Chakrabarti, A., Bahrami, A., Venkatesan, V., Vikram, A. S. V., Subramanian, J., & Mahesh, V. (2023). Efficient finite element approach to four-variable power-law functionally graded plates. *Buildings*, *13(10)*, 2577.
54. Hanabaratti, K. D., Shivannavar, A. S., Deshpande, S. N., Argiddi, R. V., Praveen, R. V. S., & Itkar, S. A. (2024). Advancements in natural language processing: Enhancing machine understanding of human language in conversational AI systems. *International Journal of Communication Networks and Information Security*, *16(4)*, 193-204.
55. Reddy, D. N., Suryodai, R., SB, V. K., Ambika, M., Muniyandy, E., Krishna, V. R., & Abdurasul, B. (2025). A Scalable Microservices Architecture for Real-Time Data Processing in Cloud-Based Applications. *International Journal of Advanced Computer Science & Applications*, *16(9)*.
56. Venkiteela, P. (2025). Modernizing opportunity-to-order workflows through SAP BTP integration architecture. *International Journal of Applied Mathematics*, *38(3s)*, 208-228.
57. Mishra, K. G., Dubey, S. K., Mani, S. A., & Pradhan, M. S. (2016). Comparative study of nanoparticles doped in Liquid Crystal Polymer System. *Journal of Molecular Liquids*, *224*, 668-671.
58. Anuprathibha, T., Praveen, R. V. S., Sukumar, P., Suganthi, G., & Ravichandran, T. (2024, October). Enhancing Fake Review Detection: A Hierarchical Graph Attention Network Approach Using Text and Ratings. In *2024 Global Conference on Communications and Information Technologies (GCCIT)* (pp. 1-5). IEEE.
59. Bhuvaneshwari, A., & Kumar, S. (2022). Domain Specific ANN Heuristic Edge Detection Algorithm for CNN based MRI Classification [DAHEDA]. *Journal of Algebraic Statistics*, *13(1)*.
60. Atmakuri, A., Sahoo, A., Behera, D. K., Gourisaria, M. K., & Padhi, S. (2024, September). Dynamic Resource Optimization for Cloud Encryption: Integrating ACO and Key-Policy Attribute-Based Encryption. In *2024 4th International Conference on Soft Computing for Security Applications (ICSCSA)* (pp. 424-428). IEEE.
61. Raja, M. W., & Nirmala, D. K. (2016). Agile development methods for online training courses web application development. *International Journal of Applied Engineering Research ISSN*, *0973-4562*.
62. Gupta, A., & Rajgopal, P. R. (2025). Cybersecurity platformization: Transforming enterprise security in an AI-driven, threat-evolving digital landscape. *International Journal of Computer Applications*, *186(80)*, 19-28.
63. Balakumar, B., & Raviraj, P. (2015). Automated Detection of Gray Matter in Mri Brain Tumor Segmentation and Deep Brain Structures Based Segmentation Methodology. *Middle-East Journal of Scientific Research*, *23(6)*, 1023-1029.
64. Joshi, S. (2021, November). Discrete Wavelet Transform Based Approach for Touchless Fingerprint Recognition. In *Proceedings of International Conference on Data Science and Applications: ICDSA 2021, Volume 1* (pp. 397-412). Singapore: Springer Singapore.
65. Byeon, H., Chaudhary, A., Ramesh, J. V. N., Reddy, D. N., Nandakishore, B. V., Rao, K. B., ... & Soni, M. (2025). Trusted Aggregation for Decentralized Federated Learning in Healthcare Consumer Electronics Using Zero-Knowledge Proofs. *IEEE Transactions on Consumer Electronics*.

66. Mubsira, M., & Niasi, K. S. K. (2018). Prediction of Online Products using Recommendation Algorithm.
67. Kemmannu, P. K., Praveen, R. V. S., & Banupriya, V. (2024, December). Enhancing Sustainable Agriculture Through Smart Architecture: An Adaptive Neuro-Fuzzy Inference System with XGBoost Model. In *2024 International Conference on Sustainable Communication Networks and Application (ICSCNA)* (pp. 724-730). IEEE.
68. Gurram, N. T., Narender, M., Bhardwaj, S., & Kalita, J. P. (2025). A Hybrid Framework for Smart Educational Governance Using AI, Blockchain, and Data-Driven Management Systems. *Advances in Consumer Research*, 2(5).
69. Patil, P. R., Parasar, D., & Charhate, S. (2024). Wrapper-based feature selection and optimization-enabled hybrid deep learning framework for stock market prediction. *International Journal of Information Technology & Decision Making*, 23(01), 475-500.
70. Sharma, P., Manjula, H. K., & Kumar, D. (2024, February). Impact of gamification on employee engagement-an empirical study with special reference to it industry in bengaluru. In *3rd International Conference on Reinventing Business Practices, Start-ups and Sustainability (ICRBSS 2023)* (pp. 479-490). Atlantis Press.
71. Rajgopal, P. R. (2025). SOC Talent Multiplication: AI Copilots as Force Multipliers in Short-Staffed Teams. *International Journal of Computer Applications*, 187(48), 46-62.
72. Niasi, K. S. K., & Kannan, E. (2016). Multi Attribute Data Availability Estimation Scheme for Multi Agent Data Mining in Parallel and Distributed System. *International Journal of Applied Engineering Research*, 11(5), 3404-3408.
73. Mishra, K. K., Dubey, S. K., & Mani, S. A. (2017). Optical characterization of inorganic nanoparticles doped in polymer dispersed liquid crystal. *Molecular Crystals and Liquid Crystals*, 647(1), 244-252.
74. Neethi, M. V., & Raviraj, P. (2025). Evaluation of convolutional neural network models' performance for estimating mango crop yield. *International Journal of Systematic Innovation*, 9(1), 1-18.
75. Mahesh, K., & Balaji, D. P. (2022). A Study on Impact of Tamil Nadu Premier League Before and After in Tamil Nadu. *International Journal of Physical Education Sports Management and Yogic Sciences*, 12(1), 20-27.
76. Praveen, R. V. S. (2024). *Data Engineering for Modern Applications*. Addition Publishing House.
77. Vijay Vikram, A. S., & Arivalagan, S. (2017). A short review on the sugarcane bagasse with sintered earth blocks of fiber reinforced concrete. *Int J Civil Eng Technol*, 8(6), 323-331.
78. Reddy, D. N., Venkateswararao, P., Patil, A., Srikanth, G., & Chinnareddy, V. (2025). DCDNet: A Deep Learning Framework for Automated Detection and Localization of Dental Caries Using Oral Imagery. *Indonesian Journal of Electrical Engineering and Informatics (IJEEI)*, 13(2).
79. Atheeq, C., Sultana, R., Sabahath, S. A., & Mohammed, M. A. K. (2024). Advancing IoT Cybersecurity: adaptive threat identification with deep learning in Cyber-physical systems. *Engineering, Technology & Applied Science Research*, 14(2), 13559-13566.
80. Palaniappan, S., Sharma, S., Radhakrishnan, M., Krishna, K. M., Joshi, S. S., Banerjee, R., & Dahotre, N. B. (2025). Process thermokinetics influenced microstructure and corrosion response in additively in-situ manufactured Ti-Nb-Sn and Ti-Nb alloys. *Journal of Manufacturing Processes*, 152, 427-441.
81. Niasi, K. S. K. (2025). Graph Neural Network-Infused Digital Twin Platform with Transfer Learning and Quantum-Safe Protocols for Resilient Power System Control and Markets.
82. Raja, M. W. (2024). Artificial intelligence-based healthcare data analysis using multi-perceptron neural network (MPNN) based on optimal feature selection. *SN Computer Science*, 5(8), 1034.
83. Praveen, R. V. S., Hundekari, S., Parida, P., Mittal, T., Sehgal, A., & Bhavana, M. (2025, February). Autonomous Vehicle Navigation Systems: Machine Learning for Real-Time Traffic Prediction. In *2025 International Conference on Computational, Communication and Information Technology (ICCCIT)* (pp. 809-813). IEEE.
84. Gandhari, S. (2025). The Feature Store Imperative: Preparing CPG Data for Machine Learning. *International Journal of Applied Mathematics*, 38(2s), 1214-1233.
85. Kumar, S., & Bhuvaneshwari, A. (2022). AN EFFICIENT BRITWARI TECHNIQUE TO ENHANCE CANNY EDGE DETECTION ALGORITHM USING DEEP LEARNING. *ICTACT Journal on Soft Computing*, 12(3).
86. Appaji, I., & Raviraj, P. (2024). Effectiveness of recent methodologies of intelligent transportation system. *International Journal of Intelligent Transportation Systems Research*, 22(1), 34-43.

87. Sahoo, P. A. K., Aparna, R. A., Dehury, P. K., & Antaryami, E. (2024). Computational techniques for cancer detection and risk evaluation. *Industrial Engineering*, 53(3), 50-58.
88. Boopathy, D., Singh, S. S., & PrasannaBalaji, D. EFFECTS OF PLYOMETRIC TRAINING ON SOCCER RELATED PHYSICAL FITNESS VARIABLES OF ANNA UNIVERSITY INTERCOLLEGIATE FEMALE SOCCER PLAYERS. *EMERGING TRENDS OF PHYSICAL EDUCATION AND SPORTS SCIENCE*.
89. Appaji, I., & Raviraj, P. (2023). Framework for simulation of vehicular communication using LSTM-based graph attention networks. *Indian J Sci Technol*, 16(16), 1230-1240.
90. Boopathy, D., & Balaji, P. (2023). Effect of different plyometric training volume on selected motor fitness components and performance enhancement of soccer players. *Ovidius University Annals, Series Physical Education and Sport/Science, Movement and Health*, 23(2), 146-154.
91. Venkatramulu, S., Guttikonda, J. B., Reddy, D. N., Reddy, Y. M., & Sirisha, M. (2025). CyberShieldDL: A Hybrid Deep Learning Architecture for Robust Intrusion Detection and Cyber Threat Classification. *Indonesian Journal of Electrical Engineering and Informatics (IJEI)*, 13(3), 645-667.
92. Usha Rani, J., & Raviraj, P. (2023). Real-time human detection for intelligent video surveillance: an empirical research and in-depth review of its applications. *SN Computer Science*, 4(3), 258.
93. Praveen, R. V. S., Raju, A., Anjana, P., & Shibi, B. (2024, October). IoT and ML for Real-Time Vehicle Accident Detection Using Adaptive Random Forest. In *2024 Global Conference on Communications and Information Technologies (GCCIT)* (pp. 1-5). IEEE.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.