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Advanced Microwave Photonic Radar Systems Integrated with Artificial Intelligence: Architectures, Algorithms, and Publishing Guidelines

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Abstract
The paradigm of modern radar systems is undergoing a profound transformation, driven by the synergistic integration of Microwave Photonics (MWP) and Artificial Intelligence (AI). Conventional electronic radar systems increasingly face insurmountable bottlenecks regarding instantaneous bandwidth, phase noise, analog-to-digital converter (ADC) sampling jitter, and signal processing speeds, particularly when operating in dense, clutter-heavy electromagnetic environments. Microwave photonics offers a revolutionary solution, leveraging the ultra-wide bandwidth, flat frequency response, low transmission loss, and electromagnetic interference (EMI) immunity of optical components to generate, transmit, and process radio frequency (RF) signals. Concurrently, the proliferation of Low-altitude, Slow-speed, and Small (LSS) targets—such as unmanned aerial vehicles (UAVs), bionic drones, and stealth autonomous systems—necessitates advanced target classification capabilities that traditional radar signal processing cannot independently provide. By integrating machine learning (ML) models and deep convolutional neural networks (DCNNs), photonic radars can autonomously detect, track, and classify complex micro-Doppler signatures and Inverse Synthetic Aperture Radar (ISAR) images with unprecedented accuracy. This comprehensive research report explores the state-of-the-art developments in AI-integrated photonic radar, including Frequency Modulated Continuous Wave (FMCW) architectures, Mode Division Multiplexing (MDM), self-interference cancellation (SIC), and True Time Delay (TTD) beamforming. Furthermore, this document serves as a rigorous structural guideline for researchers drafting manuscripts in this domain, detailing the specific formatting, nomenclature, and organizational standards required for publishing high-impact studies on AI-enhanced microwave photonics.

1. Introduction

Radar systems have historically relied on purely electronic architectures to detect, locate, and track targets. However, the operational demands of contemporary urban surveillance, aero ecology, autonomous vehicular navigation, and electronic warfare require detecting exceptionally small cross-section targets in severe urban clutter and adverse weather conditions.[1] In these complex environments, conventional RF systems are fundamentally limited by the "electronic bottleneck." For instance, modern high-resolution radars require instantaneous bandwidths exceeding 18 GHz to achieve centimetre-level range resolutions, yet state-of-the-art electronic ADCs suffer from significant root-mean-square timing jitter at femtosecond sampling rates. Furthermore, digital signal processing architectures struggle with the massive Multiply and Accumulate (MAC) operations required for real-time analysis at these frequencies. In strong clutter, the inherent phase noise of electronic oscillators masks weak signals close to zero-Doppler, severely degrading the detection of slow-moving LSS targets.

Microwave photonics (MWP) circumvents these limitations by upconverting microwave signals into the optical domain (typically around 200 THz), where a 40 GHz RF bandwidth is fractional and easily processed by optical components. Photonic radar systems enable the generation of highly stable, ultra-low phase noise signals using optical frequency combs, mode-locked lasers, and optoelectronic oscillators (OEOs). Additionally, the use of optical fibres provides transmission losses of approximately 0.0002 dB/m, which is four orders of magnitude lower than the 2 dB/m loss typical of coaxial cables, facilitating widely distributed Multi-Input Multi-Output (MIMO) and large-scale phased array networks.

The integration of Artificial Intelligence represents the next critical evolution in photonic radar, shifting the paradigm from mere detection to autonomous cognitive sensing. The high-fidelity data generated by MWP radars—such as ultra-high-resolution ISAR imagery and rich micro-Doppler spectrograms—creates ideal, high-dimensional feature spaces for machine learning classifiers.[1] Deep learning models, including YOLO-watershed hybrids and specialized DCNNs like MobileNetV2, alongside ensemble classifiers like Random Forests, have demonstrated exceptional capability in distinguishing between drones, birds, and vehicles, even under heavy fog or strong solar scintillation.[1] This report comprehensively analyses the intersection of these two domains, detailing the underlying physics, system architectures, algorithmic implementations, and the rigorous publication standards required to disseminate this interdisciplinary research effectively.

2. Prepare Your Paper Before Styling

Before formatting a manuscript detailing AI-integrated photonic radar research, authors must first write and save the content as a separate text file, completing all substantive and organizational editing prior to the application of specific formatting templates.[5] This separation of content and presentation is crucial in interdisciplinary fields where complex optical block diagrams, intricate mathematical proofs, and deep learning architectures must be meticulously documented without the distraction of typographical styling.

When preparing the manuscript, researchers must ensure that the experimental methodology is logically sequenced and scientifically sound. For example, the optical signal generation phase—such as the use of direct digital synthesis combined with analog electronic circuits to produce an intermediate frequency LFM signal—must be detailed separately from the subsequent digital signal processing and AI classification pipelines. Authors should note that text and graphic files must be kept separate until the text has been completely formatted and styled.[5] Headings should never be manually numbered; automated typesetting systems (such as LaTeX or specific word processor templates) will apply the correct hierarchical numbering algorithms.[5]

Rigorous proofreading is required to ensure that the descriptions of optical components (e.g., Mach-Zehnder modulators, Erbium-Doped Fiber Amplifiers, and Fiber Bragg Gratings) and machine learning hyperparameters (e.g., learning rates, batch sizes, and epoch limits) are accurately conveyed before any stylistic templates are applied.[8] Authors are strongly advised to limit the use of hard tabs and to avoid formatting workarounds that may conflict with publisher-specific macros.[6] The core objective during this preparatory phase is establishing a flawless scientific narrative that seamlessly bridges the physics of microwave photonics with the computational logic of artificial intelligence.

3. Abbreviations and Acronyms

The intersection of microwave photonics and artificial intelligence utilizes a highly specialized and dense lexicon. Defining these terms clearly upon their first use is critical for manuscript clarity. Authors must not mix complete spellings and abbreviations of units, and must always ensure consistency across the abstract, main text, and figures.[10] The following definitions represent the standard terminology utilized in contemporary MWP-AI research.

Acronym	Definition	Contextual Application in Photonic Radar
ADC	Analog-to-Digital Converter	The primary electronic bottleneck component improved by high-speed optical sampling and photonic time-stretch processing.
AWG	Arbitrary Waveform Generator	Hardware utilized to generate initial baseband or intermediate frequency (IF) waveforms before optical upconversion.[1]
CNN	Convolutional Neural Network	Deep learning architectures used for classifying micro-Doppler spectrograms and high-resolution ISAR images.[1]
DPMZM	Dual-Parallel Mach-Zehnder Modulator	An advanced optical modulator that enables carrier-suppressed single-sideband modulation and highly precise self-interference cancellation.[1]
FMCW	Frequency Modulated Continuous Wave	A dominant radar architecture utilizing linear frequency modulated (LFM) chirps to simultaneously determine target range and velocity.[1]
FTTM	Frequency-to-Time Mapping	An optical technique for rapid, broadband spectrum sensing using the stimulated Brillouin scattering gain spectrum.
ISAR	Inverse Synthetic Aperture Radar	A 2D/3D high-resolution imaging technique utilizing target motion, highly reliant on wideband MWP signals.[1]
LFM	Linear Frequency Modulation	Chirped waveforms used for high-resolution target ranging and radar cross-section analysis.[1]
LSS	Low-altitude, Slow-speed, Small	A category of difficult-to-detect targets (e.g., drones, birds) requiring the ultra-stable phase responses provided by photonics.[1]

MDM	Mode Division Multiplexing	A spatial multiplexing technique using orthogonal spatial modes (e.g., Laguerre-Gaussian modes) to increase transmission capacity.
MWP	Microwave Photonics	The underlying technological discipline hybridizing radio frequency engineering and optical physics.[1]
OEO	Optoelectronic Oscillator	A photonic system that generates ultra-low phase noise microwave carriers using long optical fiber delay loops.
RCS	Radar Cross Section	The measure of a target's ability to reflect radar signals, crucial for generating training data for ML models.[1]
SBS	Stimulated Brillouin Scattering	A nonlinear optical effect used for ultra-narrow-band filtering, slow-light phase shifting, and FTTM.[1]
SFDR	Spurious-Free Dynamic Range	A critical metric quantifying the fidelity, linearity, and noise floor of a microwave photonic link.
SIC	Self-Interference Cancellation	Optical techniques used to isolate weak target echo signals from powerful transmitter leakage in miniaturized radars.[1]
TTD	True Time Delay	A technique that replaces traditional phase shifters to eliminate beam squint in broadband phased array antennas.
WDM	Wavelength Division Multiplexing	The process of transmitting multiple optical carriers over a single fiber to facilitate MIMO radar operations.[1]

4. Units

The precise documentation of photonic radar performance requires a rigorous amalgamation of optical, microwave, and computational units. Strict adherence to the International System of Units (SI) and standard engineering conventions is paramount for publication.

- Authors must not mix complete spellings and abbreviations of units. For example, a magnetic flux density should be written as "Wb/m²" or "webers per square meter," but never as "webers/m²".[10]
- When quantities appear in the text without specific numerical values, the units must be spelled out entirely (e.g., "the system exhibits a delay of a few nanoseconds," not "a few ns").[10]
- A zero must always precede decimal points for values less than one to prevent misreading: use "0.25," never ".25".[10]
- Optical wavelengths are typically expressed in nanometers (nm) (e.g., 1550 nm for standard telecom bands, or 698 nm for Strontium optical lattice clocks), while radar carrier frequencies and instantaneous bandwidths are expressed in gigahertz (GHz) or megahertz (MHz).[1]
- Phase noise, a critical parameter in determining radar capability against LSS targets in clutter, is defined as the power spectral density measured relative to the carrier in a 1-Hz bandwidth, and is denoted in dBc/Hz.

- Physical measurements, such as range resolution or cross-range resolution, must be stated in centimeters (cm) or millimeters (mm) to accurately reflect the sub-meter precision capabilities of broadband MWP radars.
- Atmospheric attenuation factors, critical for modeling the robustness of ML classifiers, are measured in decibels per kilometer (dB/km), while optical transmission losses are measured in dB/m.[1]

5. Equations

Mathematical rigor is fundamental to validating the architectures of AI-integrated photonic radars. Equations must be formatted clearly using LaTeX or equivalent equation editors, with all constituent variables defined immediately following the equation's first appearance.[9]

Radar Resolution and Range Frequency

The efficacy of a photonic radar, particularly for autonomous vehicles requiring rapid decision-making, is defined by its ability to distinguish between closely spaced targets. The fundamental range resolution (R_{res}) is inversely proportional to the bandwidth (B) of the LFM signal:

$$R_{res} = \frac{c}{2B}$$

where c is the speed of light in a vacuum. Microwave photonic systems, overcoming the electronic bottleneck, routinely achieve instantaneous bandwidths of 4 GHz to 8 GHz. A 4 GHz bandwidth yields a range resolution of 3.75 cm, which is critical for generating the fine-grained, high-fidelity ISAR images required by deep Convolutional Neural Networks.[1]

In FMCW architectures, target distance is derived from the beat frequency. The range frequency (f_r) of the echo signal received from the target is represented mathematically as:

$$f_r = \frac{2 \cdot B \cdot R}{T_s \cdot c}$$

where R is the absolute range of the target from the radar, and T_s is the duration (sweep time) of the frequency chirp.

Microwave Photonic Link Performance

The up-and-down conversion that occurs in optical links can degrade the fidelity of RF signals. The purity of the link is measured by the Spurious-Free Dynamic Range (SFDR), specifically focusing on third-order intermodulation distortion. The SFDR is calculated as:

$$SFDR_3(dB \cdot Hz^{2/3}) = \frac{2}{3}$$

where OIP_3 is the third-order output intercept point and N_{out} is the noise floor of the system. A higher SFDR indicates a photonic link capable of processing weak radar echoes without them being masked by nonlinear harmonic distortions.

Optical True Time Delay (TTD) Beamforming

In conventional phased array radars, phase shifters induce a severe phenomenon known as "beam squint" when operating with broadband signals, because the pointing angle inherently depends on the signal frequency. For an array with antenna elements separated by distance d, the phase difference ($\Delta\phi$) required to steer a beam of frequency f to an angle θ is:

$$\theta = \arcsin\left(\frac{c \cdot \Delta\phi}{2\pi f \cdot d}\right)$$

To eliminate the frequency dependency (f), MWP systems utilize True Time Delay lines. In a TTD architecture, the beam direction is governed purely by the physical time delay difference ($\Delta\tau$) between elements:

$$\theta = \arcsin\left(\frac{c \cdot \Delta\tau}{d}\right)$$

This ensures that all frequency components of a broadband radar pulse point in the exact same direction, enabling frequency-independent broadband beamforming.

Photonic Self-Interference Cancellation

In miniaturized platforms like UAVs, transmitting and receiving antennas operate in close spatial proximity, causing massive transmit leakage that can saturate the receiver. Photonic-assisted self-interference cancellation (SIC) uses a DPMZM to match the amplitude and perfectly invert the phase of a reference signal against the interference signal. Under small-signal modulation, assuming the reference and interference signals are precisely matched, the output of the DPMZM ($E_{DPMZM}(t)$) containing the canceled interference can be expressed as:

$$E_{DPMZM}(t) \propto [J_0(m_1) + J_0(m_2) - J_0(m_3)]J_1(\alpha)\{\exp[j2\pi(f_c + f_0 + kt)t] + \exp[j2\pi(f_c - f_0 -$$

where m_1, m_2, and m_3 denote the modulation indices of the target echo signal, the self-interference signal, and the cancellation reference signal, respectively, and $J_n(\cdot)$ represents the n-th order Bessel function of the first kind.[1]

Weather Attenuation Modeling for AI Robustness

To ensure AI models are robust, they must be trained on radar data encompassing adverse atmospheric conditions. Rain attenuation, which degrades signal-to-noise ratios, is calculated using the Kim model:

$$A_{rain} = k \cdot r_o^a$$

where r_o is the extent of rainfall measured in mm/hr, and k and a are specific variables derived from the Marshall-Palmer distribution. Fog attenuation, which severely impacts optical wireless communication links in hybrid systems, is modeled using Mie scattering theory:

$$(\beta) = \frac{3.91}{V}\left(\frac{\lambda}{550}\right)^{-p}$$

where λ is the operational wavelength, V is visibility measured in kilometers, and p is the scattering coefficient. Training machine learning models on data modulated by these equations ensures real-world applicability in intelligent transportation systems.

6. Headings

The structural hierarchy of the manuscript must adhere to strict formatting standards to ensure readability and compatibility with automated indexing systems.[10]

- **Primary Headings:** Must be enumerated with Roman numerals and centered in standard capitalization (e.g., I. INTRODUCTION).
- **Secondary Headings:** Enumerated with capital letters, flush left, and italicized (e.g., *A. Photonic LFM Generation*).
- **Tertiary Headings:** Enumerated with Arabic numerals, indented, and italicized. Authors must not number text heads manually; the document styling software or LaTeX template should manage enumeration automatically to prevent structural errors and formatting conflicts during the final typesetting process.[5]

7. Figures and Tables

Figures and tables must be integrated logically into the text, avoiding placement before their first citation. High-resolution vector graphics are preferred for optical block diagrams and system architectures, while spectrograms and ISAR images should maintain a high DPI (dots per inch) to accurately display micro-Doppler signatures and scatter-point geometries necessary for verifying AI classification.[3]

Tables are highly effective for consolidating performance metrics of AI classifiers or MWP system parameters. They should be preferred over sparse bulleted lists to present comparative data clearly. Table 1 demonstrates the comparative performance of various machine learning classifiers evaluated on an MDM-WDM photonic radar system operating under adverse fog and solar scintillation conditions.

Classifier Algorithm	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**F1 Score (%)**	**False Discovery Rate (FDR) (%)**
Decision Tree (DT)	91.51	91.47	97.17	91.46	8.54
Extremely Randomized Trees (ERT)	90.62	90.33	96.62	90.40	9.60
Random Forest (RF)	89.95	89.50	95.77	89.62	10.38
Histogram-Based Gradient Boosting (HGB)	89.62	89.01	94.78	89.42	10.58
Extreme Gradient	85.32	84.02	94.32	84.72	15.98

Boosting (XGB)					
Adaptive Boosting (AB)	72.04	71.07	86.84	71.71	28.93

Table 1: Performance metrics of machine learning classifiers trained on FMCW photonic radar data under varying weather conditions. The Decision Tree (DT) classifier exhibits superior robustness in these specific simulated environments, maintaining the highest overall accuracy and the lowest False Discovery Rate (FDR).

Table 2 highlights the hardware performance benchmarks of a concurrent radar detection and spectrum sensing prototype, illustrating the leap in capabilities provided by MWP integration over traditional electronic systems.

Parameter	Performance Specification
Radar Operating Frequency Range	8 to 40 GHz
Instantaneous Radar Bandwidth	4 GHz
Radar Range Resolution	3.75 cm
Radar Range Error	$< \pm$ 2 cm
Radial Velocity Error	$< \pm$ 1 cm/s
Spectrum Sensing Range	0 to 40 GHz
Instantaneous Sensing Bandwidth	2 GHz
Frequency Measurement Error	$< \pm$ 7 MHz

Table 2: Key operational parameters of a microwave photonic prototype achieving simultaneous high-resolution ISAR imaging and rapid spectrum sensing via Frequency-to-Time Mapping (FTTM).

8. Some Common Mistakes

Authors documenting the intersection of photonics and AI frequently make specific stylistic and technical errors that undermine the manuscript's rigor. Adherence to standard scientific writing practices is mandatory.

- **Linguistic Errors:** The word "data" is inherently plural, not singular (e.g., "The data indicate," not "The data indicates"). The subscript for the permeability of vacuum (μ_0), and other common scientific constants, must be a numerical zero formatted as a subscript, not a lowercase letter "o".[5] Furthermore, in American English formatting, commas, semicolons, periods, question marks, and exclamation marks must be located within quotation marks only when a complete thought or name is cited, such as a title or a direct quotation.[7]

- **Technical Terminology Errors:** Authors often conflate "phase-shifting" with "true time delay." As established in the equations section, traditional electronic phase-shifters lead to severe beam squint for broadband waveforms. True time delay networks physically alter the optical path length or group delay, ensuring frequency-independent steering. Using the terms interchangeably indicates a fundamental misunderstanding of broadband array radar physics.
- **Classifier Methodology Errors:** When documenting CNN performance on radar data, authors must clearly distinguish between the training, validation, and open-field test sets. Failure to properly segment data can lead to data leakage, particularly when augmenting ISAR imagery of LSS targets.[4] Claims of "99% accuracy" without detailing the validation separation or the presence of adverse weather testing lack scientific credibility.

Artificial Intelligence and Machine Learning Integration

While the MWP hardware captures the raw, high-fidelity physics of the target environment, Machine Learning transforms this immense data into actionable, autonomous intelligence. The fusion of these two domains defines the cutting edge of surveillance and intelligent transportation.

Target Classification via Machine Learning under Adverse Weather

Autonomous vehicles and urban surveillance networks face varying weather conditions that severely attenuate signals and inject noise. To test the resilience of MWP-AI systems, researchers utilize Mode Division Multiplexing (MDM) combined with Wavelength Division Multiplexing (WDM). By utilizing orthogonal spatial modes, such as Laguerre-Gaussian modes (LG_{00} and LG_{01}) transmitted over distinct wavelengths (e.g., 1550 nm and 1550.1 nm), the system ensures robust, high-capacity signal delivery.

The backscattered data—reflecting multiple targets spaced at precise intervals—is collected under simulated adverse conditions, such as heavy fog inducing 75 dB/km of attenuation, or strong solar scintillation (10^{-6}). This complex, noisy data is then processed through supervised ML classifiers. Empirical research indicates that Decision Tree (DT) classifiers can achieve an accuracy of 91.51% and a specificity of 97.17% in these volatile conditions, outperforming complex ensemble methods like Extreme Gradient Boosting (XGB) and Adaptive Boosting (AB). The DT algorithm's deterministic hierarchical splitting effectively navigates the specific noise profiles introduced by Gamma-Gamma fading channels and Mie scattering, providing the high reliability and low False Discovery Rates (8.54%) essential for life-critical autonomous decision-making.

Deep Convolutional Neural Networks and ISAR Imagery

When detecting aerial LSS targets (e.g., civilian drones, bionic birds, RC planes), simple point-cloud detection is insufficient for threat assessment. Photonic radars capture intricate micro-Doppler signatures—such as the Helicopter Rotor Modulation (HERM) lines generated by drone blades—and render them into high-resolution Inverse Synthetic Aperture Radar (ISAR) images.

The application of Deep Convolutional Neural Networks (DCNNs) to these photonic ISAR images has yielded unprecedented classification metrics. Using a transfer learning approach with networks like MobileNetV2 on customized, augmented datasets (such as the DIAT-ISAR-sATIs dataset), researchers have achieved validation accuracies exceeding 98.67%.[4]

Furthermore, novel algorithmic frameworks, such as the Watershed YOLO approach, integrate physical electromagnetic scattering characteristics directly with geometric boundaries. This hybrid approach enables the ordered calibration of strong scatter points in ISAR imagery. By utilizing a three-stage global optimal matching strategy, the system corrects localization drift and label inconsistency, progressing beyond simple bounding-box detection to execute precise attitude inversion and motion parameter estimation of the stealthy target.[3]

9. Appendix

The appendix serves to document the exhaustive technical specifications of the datasets, experimental testbeds, and algorithmic frameworks that underpin the findings discussed in the primary text. Providing this data ensures reproducibility and peer verification.

The UoB L-Band Staring Radar Testbed

The University of Birmingham (UoB) has established a permanent, dual-node L-band staring radar facility to benchmark urban surveillance performance. The system comprises an array of 64 receivers arranged in a 4x16 grid, enabling simultaneous multiple digital beamforming over a 90° azimuth and 60° elevation field of regard. Operating at a ~2 MHz bandwidth and an ~8 kHz Pulse Repetition Frequency (PRF), the system records massive datasets of opportunistic birds and controlled drone flights in dense urban clutter. The testbed specifically evaluates the integration of ultra-low phase noise photonics oscillators—such as Menlo Microwave generator units incorporating optical frequency combs locked to cold-atom Strontium optical lattice clocks operating at 698 nm. These advanced photonics oscillators dramatically lower the noise floor close to zero-Doppler, revealing the micro-Doppler HERM lines of drones that would otherwise be completely masked by static building clutter when using conventional Phase Locked Oscillators (PLO) or GPS Disciplined Oscillators (GPSDO).

The DIAT-ISAR-sATIs Dataset Specifications

The Defense Institute of Advanced Technology (DIAT) generated the DIAT-ISAR-sATIs dataset specifically to train deep learning models on LSS targets. The dataset was captured using a Stepped Frequency Modulated Continuous Wave (SFMCW) photonic radar operating with an ultra-broadband Instantaneous Bandwidth (IBW) of 6–12 GHz.[4] The dataset comprises 4,320 primary ISAR images, which were expanded to 6,000 via data augmentation. The data is distributed across six distinct classes:

1. RC Plane
2. Mini-helicopter
3. DJI F450 Quadcopter
4. Scythe 4s Racer
5. Bionic-bird
6. Combination (Mini-helicopter + Bionic-bird).[4] Processed through a fine-tuned MobileNetV2 network, this dataset enables models to achieve a 95.56% classification accuracy in open-field empirical tests, demonstrating the robustness of combining DCNNs with ultra-broadband photonic radar data.[4]

MDM-WDM Radar Simulation Parameters

In simulations evaluating machine learning robustness under adverse weather, the MDM-WDM architecture utilized a 77 GHz RF carrier (the Short Range Radar band for autonomous vehicles) with 4 GHz of bandwidth. The optical carrier operated at 1550 nm and 1550.1 nm, multiplexing Laguerre-Gaussian modes (LG_{00} and LG_{01}). Targets were spaced at 25, 30, 60, and 75 meters. The resultant beat frequencies linearly corresponded to these ranges (e.g., 66.66 MHz for the 25m target, 200 MHz for the 75m target). The system successfully extracted these frequencies across all environmental sample scenarios, providing the robust numerical feature vectors fed into the ML classifiers..

10. Acknowledgement

Acknowledgements should be concise and recognize individuals or institutions that provided technical support, equipment, or financial backing that facilitated the research. For example, acknowledging the provision of L-band radar radomes, customized highly nonlinear fibers, or access to high-performance computing clusters for training deep learning models is appropriate. Acknowledgements should not delve into scientific analysis or restate the abstract's conclusions.

11. References

References within Main Content of the Research Paper

The References section must rigorously follow the formatting guidelines established by the specific journal or conference (e.g., IEEE). All claims, data points, and prior works mentioned in the text must be supported by a citation in this section. The list must be numbered sequentially as they appear in the text, using square brackets. Ensure that journal titles are appropriately abbreviated and italicized, and that all author names, publication years, volume numbers, issue numbers, and page ranges are accurately transcribed. Papers that have not yet been published but have been submitted should be cited as "unpublished," while those accepted for publication should be cited as "in press".[8]

References in the Reference List at the End of the Research Paper

When formatting the reference list at the end of the research paper, precision is critical to ensure automated citation trackers (such as CrossRef or Google Scholar) can index the work correctly.

1. Author Names: List all authors up to six; if there are more than six authors, use "et al." after the first author's name.[8]
2. Capitalization: Capitalize only the first word in a paper title, except for proper nouns and element symbols.[8]
3. Digital Object Identifiers (DOIs): Whenever available, include the DOI at the end of the reference to provide a persistent link to the source document.
4. Formatting Styles: Pay close attention to the punctuation separating authors, titles, and publication details. Titles of books and journals are typically italicized, while titles of conference proceedings and individual articles are set in standard type, often enclosed in quotation marks.

Example of List of References

1. S. Pan and Y. Zhang, "Microwave photonic radars," *J. Lightw. Technol.*, vol. 38, no. 19, pp. 5450-5484, Oct. 2020.
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4. S. Chaudhary, A. Sharma, K. Singh, S. Khichar, and J. Malhotra, "Highly efficient photonic radar by incorporating MDM-WDM and machine learning classifiers under adverse weather conditions," *PLoS ONE*, vol. 19, no. 4, p. e0300653, April 2024.
5. N. Akhter, A. Waghumbare, and A. B. Raj A, "A Photonic Radar Aided DCNN-Based Classification of LSS Targets Using their ISAR-Images: DIAT-ISAR-sATIs," *International Journal of Electronics and Communication Engineering*, vol. 12, no. 11, pp. 103-114, 2025.