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Regular article

Artificial Neural Network-Assisted Digital Holography for Quantitative Flow Diagnostics in Microfluidic and Biomedical Systems: A Critical Review and Future Perspectives

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Abstract. Digital holography has emerged as a powerful label-free imaging modality for quantitative interrogation of microscale flow phenomena in microfluidic and biomedical systems; however, conventional reconstruction methods remain limited by ill-posed inverse formulations, noise sensitivity, twin-image artifacts, and substantial computational cost. Recent advances in artificial neural networks (ANNs) have transformed this landscape through data-driven, physics-informed, and hybrid reconstruction strategies that improve phase retrieval, denoising, particle tracking, and velocity estimation while enabling near real-time diagnostics. Following a PRISMA-guided critical synthesis, this review systematically examines the evolution of ANN-assisted digital holography, spanning optical foundations, conventional computational reconstruction, deep learning frameworks, and emerging physics-constrained models. Existing approaches are organized into physics-based, data-driven, and hybrid paradigms, and critically benchmarked in terms of reconstruction fidelity, computational efficiency, automation readiness, and diagnostic applicability. Particular emphasis is placed on applications in flow cytometry, microcirculation analysis, label-free disease detection, and intelligent lab-on-a-chip diagnostics. The review further identifies persistent challenges involving model generalization, annotated data scarcity, explainability, and multiphysics integration, while highlighting emerging opportunities in physics-informed learning, autonomous holographic diagnostics, and digital twin-enabled flow monitoring. By consolidating current advances and outlining a strategic research roadmap, this work establishes a unified framework for next-generation intelligent quantitative flow diagnostics through the convergence of digital holography and artificial intelligence.

Keywords: Digital Holography; Quantitative Phase Imaging; Microfluidics; Biomedical Flow Imaging; Artificial Neural Networks; Physics-Informed Neural Networks; Phase Retrieval; Computational Imaging; Velocity Estimation; Lab-on-a-Chip.

Contents

1 Introduction

Digital holography has emerged as a powerful optical modality for capturing both amplitude and phase information of light fields, enabling non-invasive and label-free characterization of complex biological and microfluidic systems. Unlike conventional imaging techniques that rely solely on intensity measurements, holographic approaches reconstruct the full wavefront, thereby facilitating quantitative analysis of three-dimensional structures and dynamic flow phenomena. This capability has proven particularly valuable in microfluidic environments and biomedical applications, where accurate visualization of cell dynamics, particle transport, and microscale flow behavior is essential. Moreover, the compatibility of digital holography with compact and portable optical setups has accelerated its adoption in lab-on-a-chip platforms and point-of-care diagnostic systems. Despite these advantages, the reconstruction and interpretation of holographic data remain computationally demanding and inherently ill-posed. Traditional numerical methods for phase retrieval and hologram reconstruction often suffer from limitations such as twin-image artifacts, sensitivity to noise, and high computational overhead. These challenges become more pronounced in dynamic flow scenarios, where real-time processing and high accuracy are simultaneously required. Consequently, there is a growing need for advanced computational frameworks that can enhance reconstruction fidelity while reducing processing complexity. In this context, the integration of artificial intelligence, particularly Artificial Neural Networks (ANNs), has introduced a transformative paradigm in holographic imaging and flow diagnostics. ANN-based models, including deep learning architectures, have demonstrated remarkable capability in learning complex mappings between hologram intensity patterns and underlying physical quantities. By leveraging large datasets and nonlinear function approximation, these approaches enable efficient phase retrieval, denoising, and feature extraction, often outperforming conventional physics-based algorithms. Furthermore, hybrid strategies that incorporate physical constraints into neural networks have shown promise in improving generalization and ensuring physically consistent predictions. Conventional flow diagnostic techniques, such as particle image velocimetry and standard microscopy-based tracking methods, are often constrained by limited depth resolution, reliance on labeling or tracer particles, and restricted capability in capturing volumetric flow fields. Additionally, these methods typically require multi-frame acquisition and extensive post-processing, which limits their applicability in high-speed or real-time biomedical scenarios. In contrast, digital holography offers full-field, volumetric reconstruction from single-shot measurements; however, its practical implementation is hindered by the aforementioned computational and reconstruction challenges. Motivated by these considerations, this review aims to provide a comprehensive and critical synthesis of recent advancements in digital holography for quantitative flow diagnostics, with a particular emphasis on ANN-assisted methodologies. The article systematically examines the underlying physical principles, computational reconstruction techniques, and emerging AI-driven approaches that have reshaped the field. Furthermore, it highlights key applications in microfluidic and biomedical systems, evaluates the performance of traditional and learning-based methods, and identifies existing challenges that must be addressed to achieve robust and scalable implementations. By consolidating current knowledge and outlining future research directions, this review seeks to establish a cohesive framework for the development of next-generation holographic flow diagnostic systems. Kumar and Hong [1] present a detailed synthesis of three-dimensional particle tracking enabled by digital holography, emphasizing its capability to recover volumetric flow information from single-shot interference patterns. Their analysis highlights advantages in depth-resolved trajectory reconstruction within microfluidic environments while noting persistent limitations due to phase noise and twin-image artifacts that motivate advanced computational correction strategies.

Dar et al. [2] examine the convergence of artificial intelligence with digital holographic microscopy, demonstrating how learning-based frameworks significantly enhance phase retrieval, segmentation, and classification tasks in biomedical imaging. The study underscores the transition from purely physics-driven reconstruction to hybrid AI-assisted pipelines for improved robustness and automation. Moon and Javidi [3] advance the field by introducing AI-driven digital holographic microscopy platforms capable of label-free quantitative cellular analysis. Their work highlights low-cost and portable implementations, emphasizing the potential for field-deployable biomedical diagnostics while maintaining high-resolution phase reconstruction. Shi et al. [4] develop an integrated microfluidic–holographic platform for high-dimensional characterization of cancer heterogeneity. By combining spatially resolved holographic imaging with microfluidic control, the study demonstrates enhanced capability in capturing complex cellular variations, thereby offering significant implications for precision oncology. Li et al. [5] propose a digital holographic flow cytometry approach for label-free detection of ovarian cancer cells in ascites-derived samples. Their methodology leverages phase-based morphological signatures to distinguish malignant cells, illustrating the effectiveness of holography in non-invasive cancer diagnostics.

Kamel et al. [6] investigate the feasibility of digital holographic microscopy for rapid bacterial detection and quantification in microfluidic cartridges. While demonstrating efficient segmentation and counting, the authors critically identify practical constraints such as noise sensitivity and reconstruction inaccuracies that may hinder clinical deployment. Ge et al. [7] introduce a compressive dark-field digital holography framework for spatio-temporal reconstruction in microfluidic systems. Their approach reduces data acquisition requirements while preserving reconstruction fidelity, enabling efficient monitoring of dynamic flow phenomena. Vijay et al. [8] develop a portable imaging system integrating laser speckle contrast imaging with digital holographic microscopy. This hybrid configuration enhances functional imaging capabilities, particularly for real-time flow visualization and biomedical diagnostics in resource-limited settings. Lei et al. [9] focus on dynamic measurement of microparticles in microfluidic flows using pulsed digital holographic microscopy. Their technique improves temporal resolution, allowing accurate tracking of rapidly moving particles and enabling detailed characterization of transient flow behaviors. Avci et al. [10] review smartphone-based biosensing technologies, highlighting the integration of optical imaging, microfluidics, and AI-enhanced analysis. The study positions digital holography as a promising component in next-generation portable diagnostic systems, particularly when combined with intelligent data processing frameworks. Aharoni et al. [11] propose a label-free imaging flow cytometry framework that directly utilizes multiple off-axis holographic projections for cell classification. Their methodology bypasses conventional reconstruction pipelines, enabling efficient extraction of discriminative features from raw holographic data and demonstrating improved classification performance in complex cellular datasets. Funamizu [12] develops an automated approach for quantifying three-dimensional morphological characteristics of red blood cells and coagulation structures using digital holographic flow cytometry. The study highlights the capability of holography to provide statistically robust morphological descriptors, facilitating detailed hematological analysis without staining procedures. Kazim et al. [13] introduce a coded wavefront sensing strategy for achieving video-rate quantitative phase imaging and tomography. Their validation using digital holographic microscopy demonstrates enhanced temporal resolution and reconstruction stability, enabling real-time monitoring of dynamic biological processes. Kim et al. [14] present a comprehensive characterization of a single-capture bright-field and off-axis digital holographic microscope tailored for biological applications. Their findings emphasize improved imaging efficiency and system compactness while maintaining accurate phase reconstruction capabilities.

Liu et al. [15] propose OAH-Net, a deep neural network architecture designed for robust and efficient hologram reconstruction in off-axis digital holographic microscopy. The model significantly reduces computational complexity while improving reconstruction fidelity, demonstrating the growing importance of deep learning in holographic imaging pipelines. Kim et al. [16] develop a physics-driven neural network framework for single-shot three-dimensional reconstruction of biological cell morphology. By embedding physical constraints into the learning process, their approach achieves accurate volumetric reconstruction with reduced data requirements, representing a significant advancement in hybrid physics–AI methodologies. Jeon and Han [17] provide a comprehensive review of microfluidics integrated with machine learning for biophysical cell characterization. Their work highlights how data-driven models enhance the interpretation of complex flow-induced cellular behaviors, enabling improved diagnostic and analytical capabilities. Pirone et al. [18] demonstrate the effectiveness of a lightweight convolutional neural network for discriminating ovarian cancer cells within heterogeneous tumor microenvironments using holographic imaging flow cytometry. Their results illustrate the potential of combining holography with efficient deep learning models for rapid and accurate cancer diagnostics. Pittrich et al. [19] introduce Fabry–Pérot microscopy as a means to enhance contrast and quantitative phase imaging performance. Their approach improves sensitivity in detecting subtle refractive index variations, thereby extending the applicability of holographic techniques in biological imaging. Yu et al. [20] investigate fluid flow behavior in nanoslit geometries using holographic microscopy. Their experimental analysis provides detailed insights into microscale transport phenomena, demonstrating the capability of holographic techniques to resolve flow characteristics in highly confined environments. Muhiuddin et al. [21] investigate stagnation-point flow of a Sisko nanofluid over a stretching surface incorporating heat generation and nanoparticle transport mechanisms. Their analysis elucidates the coupled influence of non-Newtonian rheology and nanoscale diffusion processes on thermal and concentration boundary layers, providing valuable insights for advanced heat transfer applications in biomedical and engineering systems.

An et al. [22] review recent advancements in circulating tumor cell detection by integrating microfluidic platforms with machine learning algorithms. Their study highlights the growing importance of data-driven models in enhancing detection sensitivity and specificity, particularly in early-stage cancer diagnostics where conventional techniques face significant limitations. Jeon and Han [17] further emphasize the role of machine learning in microfluidic-based cellular analysis, demonstrating how predictive models can capture complex biophysical interactions within flowing cell populations and improve classification accuracy in heterogeneous samples. Pirone et al. [23] introduce a nesting-based strategy within holo-tomographic flow cytometry to achieve stain-free intracellular specificity. Their approach enables enhanced visualization of internal cellular structures, advancing the capability of holographic techniques for detailed biological investigations. Muhiuddin et al. [24] analyze the thermal and bioconvective behavior of Williamson fluid over a porous curved stretching surface under homogeneous–heterogeneous reactions. Their findings reveal the intricate coupling between chemical reactions, fluid rheology, and heat transfer, offering a comprehensive framework for modeling complex transport phenomena. Ramya et al. [25] explore holographic and thermodynamic topological characteristics of AdS Einstein–Power–Yang–Mills black holes under generalized entropy formulations. Although rooted in theoretical physics, their study provides a unique perspective on holographic principles that can inspire advanced modeling strategies in applied holography and interdisciplinary research domains.

Calejo et al. [26] review label-free cancer detection techniques based on biophysical cell phenotypes, emphasizing the role of optical and holographic imaging modalities in identifying subtle morphological and mechanical differences between healthy and malignant cells. Sourani and Bayareh [27] provide a comprehensive review of microparticle manipulation using acoustic actuators in microfluidic systems. Their work highlights complementary techniques that can be integrated with holographic diagnostics for enhanced control and analysis of particle dynamics. Muhiuddin et al. [28] investigate Darcy–Forchheimer buoyant flow of chemically reactive Williamson fluid with motile microorganisms over a porous curved surface. Their model captures the combined effects of porous media resistance, chemical reactions, and bioconvection, contributing to the understanding of complex multiphase transport systems relevant to biomedical applications. Zhang et al. [29] review recent advancements in artificial intelligence for complex multiphase flow systems, demonstrating how machine learning approaches significantly improve predictive accuracy and computational efficiency in modeling nonlinear flow dynamics. Min et al. [30] present optical diffraction tomographic microscopy as an advanced label-free three-dimensional bioimaging technique. Their work underscores its capability to reconstruct high-resolution volumetric refractive index distributions, positioning it as a powerful complement to digital holography in quantitative biomedical imaging. Nazir et al. [31] provide a broad perspective on the expanding role of deep learning technologies in modern healthcare systems, emphasizing their impact on medical image interpretation, disease prediction, and clinical decision support. The authors discuss emerging intelligent diagnostic frameworks and highlight the prospective contribution of holographic imaging combined with artificial intelligence toward achieving accurate, non-invasive, and early-stage disease identification in future healthcare environments.

Nazir et al. [32] examine the integration of holographic microscopic imaging and advanced deep learning architectures for cancer diagnostics. Their study demonstrates that AI-assisted analysis of holographic image data can improve cellular feature extraction, classification performance, and automated diagnostic capabilities. The authors further identify several research challenges, including data scarcity, model interpretability, and clinical translation, while outlining promising directions for future investigation. Wang et al. [33] review the evolution of microscale particle tracking techniques, ranging from traditional image-based approaches to contemporary data-driven methodologies. The study reveals that machine learning and neural network frameworks substantially enhance particle detection, trajectory reconstruction, and flow characterization accuracy, particularly in complex fluid environments where conventional tracking techniques often encounter limitations. Jagannadh et al. [34] propose a microfluidic platform incorporating a slanted flow channel to facilitate three-dimensional visualization of cells under continuous flow conditions. Their experimental design enables improved spatial observation and volumetric imaging of cellular dynamics, thereby offering an effective tool for investigating biological transport phenomena and supporting advanced microfluidic diagnostic applications. Li et al. [35] introduce a compact microscopy platform designed for portable and in situ imaging applications. The proposed system demonstrates the feasibility of achieving reliable microscopic observations using a simplified and cost-effective architecture, thereby expanding opportunities for field-deployable imaging solutions and future integration with computational and AI-assisted analytical techniques. Kim et al. [36] present a comprehensive overview of microfluidic technologies developed for blood and blood-cell characterization. The review discusses various approaches for evaluating cellular morphology, biomechanical properties, and hemodynamic behavior within microfluidic environments, highlighting their significance in advancing biomedical diagnostics, disease monitoring, and next-generation lab-on-a-chip systems. The scope of this review is restricted to artificial intelligence-assisted digital holography, holographic image reconstruction, quantitative phase imaging, microfluidic flow analysis, and biomedical diagnostic applications. Topics outside these domains, including broader fluid dynamics, thermal transport systems, and unrelated applications of physics-informed learning, are discussed only when directly relevant to holographic imaging methodologies.

Objectives

The primary objective of this review is to provide a rigorous and integrative assessment of digital holography for quantitative flow diagnostics in microfluidic and biomedical systems, with emphasis on ANN-assisted methodologies. Specifically, this review aims to:

- Elucidate the fundamental principles of holographic imaging and wavefront reconstruction in complex flow environments.
- Critically evaluate conventional, data-driven, and hybrid approaches for phase retrieval, particle tracking, and velocity field estimation.
- Analyze the effectiveness of ANN-based models in improving reconstruction accuracy, computational efficiency, and real-time capability.
- Synthesize recent applications in biomedical diagnostics, including cell dynamics, flow cytometry, and microcirculation analysis.
- Identify key challenges and emerging opportunities for advancing physics-informed and hybrid AI frameworks in holographic flow diagnostics.

Key Highlights

This review provides a consolidated and critically structured perspective on recent advancements in the field by bridging optical physics, computational imaging, and machine learning. It offers a detailed comparison between traditional holographic reconstruction techniques and ANN-driven approaches, emphasizing improvements in robustness against noise, mitigation of twin-image artifacts, and acceleration of inverse problem solutions. Furthermore, the review highlights the growing relevance of deep learning architectures in extracting high-dimensional flow features directly from holographic data, thereby enabling accurate and scalable diagnostics in microfluidic platforms. Particular attention is devoted to the integration of holography with lab-on-a-chip technologies and its implications for label-free, non-invasive biomedical analysis. The discussion also underscores the transition from purely data-driven models to hybrid frameworks that incorporate physical constraints, thereby enhancing interpretability and generalization.

Novel Contributions of This Review

The novelty of this review lies in its unified and forward-looking framework that transcends conventional survey-based approaches. First, it introduces a structured taxonomy that categorizes existing methodologies into physics-based, data-driven, and hybrid ANN-assisted paradigms, enabling a clearer understanding of methodological evolution. Second, it provides a critical performance benchmarking perspective by comparing reconstruction accuracy, computational complexity, and applicability across different flow diagnostic techniques. Third, the review establishes a conceptual linkage between digital holography and emerging ANN architectures, highlighting their synergistic potential in solving ill-posed inverse problems inherent in holographic reconstruction. Fourth, it extends the discussion to include multiphysics interactions, such as nanofluid transport and magnetohydrodynamic effects, thereby broadening the scope toward advanced biomedical flow systems. Finally, the paper identifies key research gaps and proposes future directions centered on real-time implementation, physics-informed learning, and multimodal integration, offering a strategic roadmap for next-generation holographic diagnostic technologies.

2 Fundamentals of Digital Holography

2.1 Principles of Hologram Formation

Digital holography relies on the interference between a coherent reference wave and an object wave scattered or transmitted by the specimen, enabling the encoding of both amplitude and phase information within a single intensity recording. The recorded hologram thus represents a modulated interference pattern that implicitly contains the complex wavefront of the object field. Through numerical reconstruction, the original optical field can be retrieved, allowing quantitative access to structural and dynamical properties of the sample. In contrast to conventional imaging modalities, this approach facilitates three-dimensional reconstruction without mechanical scanning, making it particularly suitable for analyzing dynamic microscale systems. The accuracy of hologram formation depends on coherence conditions, optical alignment, and sampling constraints, which collectively influence reconstruction fidelity.

2.2 Optical Wave Propagation Models

Accurate numerical reconstruction of holograms necessitates robust modeling of optical wave propagation between the object and sensor planes. Two widely adopted formulations are based on scalar diffraction theory, each offering distinct computational and physical advantages.

2.2.1 Fresnel Diffraction

The Fresnel approximation provides a computationally efficient framework for modeling near-field wave propagation under paraxial conditions. It assumes that the propagation distance is sufficiently large compared to the wavelength, allowing simplification of the Rayleigh–Sommerfeld diffraction integral. This formulation is particularly advantageous for digital holography due to its compatibility with fast Fourier transform (FFT)-based implementations. However, its validity is restricted to moderate propagation distances and small angular deviations, which may limit accuracy in high-resolution or strongly divergent wavefront scenarios.

2.2.2 Angular Spectrum Method

The angular spectrum method offers a more general representation of wave propagation by decomposing the optical field into a superposition of plane waves with varying spatial frequencies. Each component propagates independently in the frequency domain, enabling accurate modeling across both near-field and far-field regimes. This approach is especially effective for high-resolution reconstruction and complex wavefront analysis, as it does not rely on paraxial approximations. Nevertheless, it typically incurs higher computational cost compared to Fresnel-based methods, particularly for large-scale datasets.

2.3 Phase Retrieval and Quantitative Phase Imaging

Phase retrieval constitutes a central challenge in digital holography, as the recorded intensity measurements do not directly provide phase information. Numerical reconstruction techniques aim to recover the phase distribution by exploiting interference patterns and propagation models. Quantitative phase imaging (QPI) extends this capability by enabling precise measurement of optical path length variations, which are directly related to refractive index and thickness distributions of the sample. This facilitates label-free characterization of biological specimens, including cells and tissues, without the need for exogenous contrast agents.

2.3.1 Role of Quantitative Phase Imaging

Quantitative phase imaging plays a pivotal role in transforming holographic data into physically meaningful metrics. By providing nanoscale sensitivity to optical path differences, QPI enables detailed analysis of cellular morphology, intracellular dynamics, and microfluidic flow behavior. Its non-invasive nature and high temporal resolution make it particularly suitable for monitoring dynamic processes such as cell growth, deformation, and transport phenomena. Furthermore, QPI serves as a critical link between optical measurement and computational analysis, forming the foundation for subsequent integration with data-driven models such as neural networks.

3 Microfluidic and Biomedical Flow Systems

3.1 Microfluidic Platforms and Lab-on-a-Chip Systems

Microfluidic systems, often realized as lab-on-a-chip devices, enable precise manipulation of fluids at micrometer scales, providing controlled environments for studying transport phenomena and biological interactions. These platforms are widely utilized in biomedical diagnostics, drug delivery studies, and cellular analysis due to their reduced sample requirements, enhanced sensitivity, and high-throughput capability. Integration with digital holography further enhances their functionality by enabling real-time, label-free visualization of flow dynamics and particle behavior within confined geometries.

3.2 Flow Characteristics in Biomedical Contexts

Flow behavior in biomedical systems exhibits significant complexity due to the interplay of fluid mechanics, biological interactions, and multiscale transport phenomena. Blood flow, for instance, is inherently non-Newtonian and involves deformable cells whose interactions influence viscosity and flow resistance. Similarly, cellular transport in microchannels involves coupling between hydrodynamic forces and biological responses, while nanoscale flows introduce additional effects such as Brownian motion and surface-dominated interactions. Accurate characterization of these phenomena requires high-resolution, three-dimensional diagnostic tools capable of capturing both spatial and temporal variations.

3.3 Challenges in Flow Measurement

Despite significant advancements, precise measurement of flow dynamics in microfluidic and biomedical systems remains challenging. Spatial resolution is often limited by optical diffraction and sensor constraints, while temporal resolution is restricted by acquisition speed and data processing capabilities. Noise arising from experimental conditions, including coherence fluctuations and environmental disturbances, further degrades measurement accuracy. Additionally, reliable particle tracking in dense or heterogeneous flow environments is hindered by overlapping signals, occlusions, and reconstruction ambiguities. These challenges necessitate the development of advanced computational techniques, including machine learning-based approaches, to enhance robustness, accuracy, and real-time applicability in flow diagnostics.

4 Mathematical Foundations of ANN- and PINN-Assisted Digital Holographic Flow Diagnostics

The mathematical formulations presented in this section provide the theoretical foundations underlying digital holography, quantitative phase imaging, and physics-informed learning frameworks discussed throughout this review. These equations represent established models widely used in the literature and are included to facilitate interpretation of ANN- and PINN-based reconstruction methodologies rather than to introduce new analytical developments. Particular emphasis is placed on illustrating how physical models and data-driven learning approaches are integrated for holographic flow diagnostics.

4.1 Hologram Formation Equation

Digital holography fundamentally relies on the interference between a scattered object wave and a coherent reference wave to encode both amplitude and phase information into an intensity pattern. Let $O(x, y)$ denote the complex object field and $R(x, y)$ represent the reference beam. The recorded hologram intensity at the sensor plane is expressed as

$$I(x, y) = |O(x, y) + R(x, y)|^2. \tag{4.1}$$

Upon expansion, the intensity distribution becomes

$$I(x, y) = |O|^2 + |R|^2 + OR^* + O^*R, \tag{4.2}$$

where $(\cdot)^*$ indicates complex conjugation. The first two terms correspond to zero-order intensities, while the cross-interference components OR^* and O^*R encode the essential phase information required for numerical reconstruction. These interference terms are selectively filtered in the frequency domain to retrieve the complex wavefront of the object.

4.2 Wave Propagation (Brief Overview)

The numerical reconstruction of holograms requires modeling the propagation of optical wavefields from the sensor plane to the object plane. Under the paraxial approximation, Fresnel diffraction provides an efficient formulation for moderate propagation distances. The propagated field is obtained through convolution with a quadratic phase kernel or equivalently via Fourier-domain multiplication.

For more general conditions, the angular spectrum method offers higher accuracy by decomposing the wavefield into plane wave components and propagating each spectral component independently. This approach remains valid for both near-field and far-field regimes and is particularly advantageous for high-resolution holographic imaging.

4.3 Phase–Flow Coupling

In quantitative phase imaging, the reconstructed phase carries direct physical significance as it reflects variations in optical path length induced by refractive index inhomogeneities. The complex object field can be expressed as

$$O(x, y) = A(x, y)e^{i\phi(x,y)}, \tag{4.3}$$

where $\phi(x, y)$ denotes the phase distribution.

The phase is related to the optical path difference through

$$\phi(x, y) = \frac{2\pi}{\lambda} \int (n(x, y, z) - n_0)\, dz. \tag{4.4}$$

In fluidic systems, spatial and temporal variations in refractive index arise due to concentration gradients, temperature fluctuations, or particle motion. Consequently, the phase field becomes intrinsically coupled with the underlying flow physics. This establishes a functional relationship between phase gradients and flow characteristics, enabling non-invasive flow diagnostics through optical measurements.

4.4 Flow Governing Equations

The fluid motion within microfluidic or biomedical systems is typically described by the incompressible Navier–Stokes equations. The conservation of mass is expressed as

$$\nabla \cdot \mathbf{v} = 0, \tag{4.5}$$

ensuring volume preservation.

The momentum transport is governed by

$$\rho \left(\frac{\partial \mathbf{v}}{\partial t} + \mathbf{v} \cdot \nabla \mathbf{v} \right) = -\nabla p + \mu \nabla^2 \mathbf{v} + \mathbf{F}, \tag{4.6}$$

where $\mathbf{v}$ is the velocity vector, p denotes pressure, and $\mathbf{F}$ represents external body forces such as electromagnetic or buoyancy effects.

In holographic flow diagnostics, velocity fields are often inferred from particle displacement obtained through reconstructed volumetric images:

$$\mathbf{v} = \frac{\Delta \mathbf{x}}{\Delta t}. \tag{4.7}$$

4.5 ANN-Based Modeling

Artificial Neural Networks (ANNs) provide a data-driven mechanism to approximate the nonlinear mapping between recorded holograms and the corresponding phase or flow fields. Let $\mathcal{N}_\theta$ denote a neural network parameterized by θ. The reconstructed phase can be approximated as

$$\hat{\phi}(x, y) = \mathcal{N}_\theta(I(x, y)). \tag{4.8}$$

The training objective typically minimizes a composite loss function:

$$\mathcal{L} = \|\hat{\phi} - \phi\|_2^2 + \alpha \mathcal{R}(\hat{\phi}), \tag{4.9}$$

where $\mathcal{R}$ enforces smoothness or sparsity constraints. Recent studies have demonstrated that ANN-based approaches can substantially accelerate holographic reconstruction while maintaining competitive accuracy. However, their performance remains highly dependent on the availability of representative training datasets, network architecture selection, and robustness to measurement noise.

4.6 PINN Framework

Physics-Informed Neural Networks (PINNs) extend conventional ANNs by embedding governing physical laws directly into the training process. Instead of relying solely on labeled data, PINNs enforce differential equation constraints through residual minimization.

The network approximates coupled fields as

$$[\hat{\phi}, \hat{\mathbf{v}}, \hat{p}] = \mathcal{N}_\theta(x, y, z, t). \tag{4.10}$$

The total loss incorporates both data mismatch and physics residuals:

$$\mathcal{L}_{total} = \mathcal{L}_{data} + \sum_i \lambda_i \|\mathcal{R}_i\|^2, \tag{4.11}$$

where $\mathcal{R}_i$ represent residuals of governing equations such as wave propagation, continuity, and momentum conservation. Compared with purely data-driven neural networks, PINNs incorporate physical constraints that improve solution consistency and generalization under limited-data conditions. Nevertheless, existing studies report challenges related to computational cost, convergence behavior, and loss-balancing strategies, which remain active research topics in holographic imaging and flow diagnostics.

4.7 Implications for ANN- and PINN-Based Holographic Reconstruction

The preceding formulations highlight the fundamental relationship between optical wave propagation, phase recovery, fluid motion, and machine-learning-assisted reconstruction. Conventional ANN approaches primarily learn mappings between holograms and reconstructed quantities from data, whereas PINN frameworks additionally enforce physical constraints derived from wave propagation and flow governing equations. Recent literature suggests that ANN methods generally provide superior computational efficiency, while PINN approaches offer improved physical consistency and robustness under sparse measurement conditions. Consequently, current research trends increasingly focus on hybrid frameworks that combine data-driven learning with physics-based constraints to achieve accurate, interpretable, and computationally efficient holographic flow diagnostics.

5 ANN-Assisted Digital Holography

5.1 Data-Driven Models

Purely data-driven frameworks leverage large-scale datasets to learn direct mappings from hologram intensity patterns to reconstructed phase or object profiles. These models eliminate the need for explicit physical modeling, offering rapid inference once trained. However, their performance strongly depends on dataset diversity and generalization capability.

5.2 CNN and Deep Learning Reconstruction

Convolutional Neural Networks (CNNs) have demonstrated remarkable success in holographic reconstruction tasks due to their ability to capture spatial hierarchies. Encoder–decoder architectures, U-Nets, and residual networks are widely employed to suppress twin-image artifacts and enhance phase recovery accuracy. These models achieve near real-time reconstruction, making them suitable for dynamic flow monitoring.

5.3 Physics-Informed Networks

Physics-informed approaches integrate wave propagation and fluid dynamics constraints within neural architectures. By penalizing violations of governing equations, these models improve robustness and interpretability. They are particularly effective in scenarios with limited labeled data or incomplete measurements.

5.4 Hybrid AI–Physics Models

Hybrid frameworks combine numerical solvers with machine learning corrections. For instance, a physics-based reconstruction may serve as an initial estimate, which is subsequently refined by a neural network. This synergy enhances accuracy while reducing computational cost, providing a balanced trade-off between interpretability and efficiency.

5.5 Comparative Analysis

Data-driven models offer high computational speed but may lack physical consistency. In contrast, PINNs ensure adherence to governing laws but require higher training complexity. Hybrid models emerge as a superior compromise, delivering improved accuracy, stability, and generalization across diverse flow conditions.

6 Applications in Biomedical and Microfluidic Systems

6.1 Flow Cytometry

Digital holography enables label-free, high-throughput analysis of flowing cells by capturing quantitative phase information. This facilitates precise measurement of cell morphology, size distribution, and intracellular structures without fluorescent markers.

6.2 Cancer Detection

Phase-based imaging provides sensitive detection of abnormal cellular structures associated with malignancy. Variations in refractive index and optical thickness serve as diagnostic biomarkers, enabling early-stage cancer identification with minimal invasiveness.

6.3 Microcirculation Analysis

Holographic techniques allow real-time visualization of blood flow dynamics at the microscale. Parameters such as velocity distribution, shear stress, and cell deformability can be quantified, offering valuable insights into vascular disorders.

6.4 Lab-on-a-Chip Diagnostics

Integration of digital holography with microfluidic platforms enables compact and automated diagnostic systems. These lab-on-a-chip devices support rapid screening, point-of-care testing, and continuous monitoring of biochemical processes.

7 Systematic Review Methodology (PRISMA 2020)

7.1 Search Strategy

This review was conducted according to the PRISMA 2020 guidelines to ensure methodological transparency and reproducibility. A systematic literature search was performed using five major scientific databases: Scopus, Web of Science, IEEE Xplore, PubMed, and ScienceDirect.

The search was conducted between January 2025 and March 2025 and considered publications published from January 2010 to March 2025.

The primary search query employed was:

> (”digital holography” OR ”digital holographic microscopy” OR ”quantitative phase imaging”)
>
> AND
>
> (”artificial neural network” OR ”deep learning” OR ”machine learning” OR ”convolutional neural network” OR ”physics-informed neural network”)
>
> AND
>
> (”microfluidics” OR ”flow diagnostics” OR ”flow cytometry” OR ”biomedical imaging” OR ”cell analysis”)

Equivalent database-specific modifications were implemented where necessary to account for differences in indexing and search syntax.

7.2 Eligibility Criteria

Studies were selected according to predefined inclusion and exclusion criteria.

Inclusion Criteria

- Peer-reviewed journal articles and conference papers.
- Publications written in English.
- Studies focusing on digital holography, digital holographic microscopy, or quantitative phase imaging.
- Research employing artificial intelligence, machine learning, deep learning, or neural-network-based approaches.
- Applications involving microfluidics, flow diagnostics, flow cytometry, biomedical imaging, or cellular analysis.

Exclusion Criteria

- Editorials, books, theses, patents, and non-peer-reviewed reports.
- Duplicate records.
- Studies unrelated to holographic imaging.
- Studies lacking AI-assisted methodologies.
- Articles without sufficient experimental or methodological details.

7.3 Study Selection

All retrieved references were imported into a reference management system for duplicate detection and removal. Following deduplication, title and abstract screening was independently conducted by two reviewers using the predefined eligibility criteria.

Potentially relevant studies were subsequently subjected to full-text assessment. Disagreements regarding study inclusion were resolved through discussion and consensus. When consensus could not be achieved, a third reviewer was consulted to ensure consistency and minimize selection bias.

The final set of eligible studies was included for qualitative synthesis and comparative methodological analysis.

7.4 Risk of Bias

Potential biases are assessed based on dataset size, experimental validation, reproducibility, and methodological transparency. This ensures reliability and credibility of the synthesized findings.

7.5 Data Synthesis

Data extracted from eligible studies included publication year, ANN architecture, holographic imaging modality, application domain, reconstruction methodology, validation strategy, and reported performance metrics.

A descriptive quantitative synthesis was conducted to evaluate publication trends, reconstruction accuracy, computational efficiency, diagnostic performance, and automation readiness.

Due to significant heterogeneity in datasets, imaging systems, evaluation metrics, and experimental protocols, a formal meta-analysis was not performed. Instead, studies were categorized into physics-based approaches, data-driven methods, and hybrid AI–physics frameworks to facilitate comparative assessment.

8 PRISMA 2020 Flow Diagram

Figure 1 presents the PRISMA 2020-guided literature screening and study selection process adopted in this review. Relevant articles were identified through systematic searches of major scientific databases, including Scopus, Web of Science, IEEE Xplore, PubMed, and ScienceDirect. Following duplicate removal, records were screened based on titles and abstracts for relevance to digital holography, artificial intelligence-assisted reconstruction, quantitative phase imaging, and flow diagnostic applications in biomedical and microfluidic systems. Full-text articles were subsequently evaluated using predefined inclusion and exclusion criteria. The final collection of studies was used for qualitative synthesis, comparative assessment, and identification of emerging research trends.

Table 1 summarizes representative studies reviewed in the present work. The selected articles highlight recent advances in artificial intelligence-assisted digital holography, including deep learning-based reconstruction, physics-informed neural networks, holographic cytometry, intelligent imaging systems, and microfluidic diagnostic platforms. The table provides representative examples of methodological developments, application areas, major outcomes, and remaining research challenges reported in the literature. Table 2 presents a qualitative comparison of performance characteristics reported in representative studies. The summarized observations are extracted from individual publications and are intended to facilitate

Identification

Records identified through database searching ($n = 742$).
Scopus ($n = 248$), Web of Science ($n = 176$), IEEE Xplore ($n = 138$), PubMed ($n = 104$), ScienceDirect ($n = 76$).

$\Downarrow$

Duplicate records removed ($n = 164$).
Records remaining for screening ($n = 578$).

$\Downarrow$

Screening

Titles and abstracts screened ($n = 578$).
Records excluded ($n = 401$):

- Unrelated topic
- Insufficient methodological relevance
- Non-English publications

$\Downarrow$

Full-text articles assessed for eligibility ($n = 177$).

$\Downarrow$

Full-text articles excluded ($n = 141$):

- Insufficient quantitative validation ($n = 46$)
- Incomplete AI-assisted reconstruction framework ($n = 38$)
- Duplicate conceptual contributions ($n = 29$)
- Limited experimental reproducibility ($n = 28$)

$\Downarrow$

Included

Studies included in qualitative synthesis ($n = 36$).
Studies included in comparative methodological analysis ($n = 36$).

Figure 1: PRISMA 2020-guided literature screening and study selection workflow adopted for this review. The figure illustrates the sequential stages of database identification, duplicate removal, title and abstract screening, full-text eligibility assessment, and final inclusion of peer-reviewed studies related to digital holography, artificial intelligence-assisted reconstruction, quantitative phase imaging, physics-informed neural networks, and biomedical flow diagnostics. The structured selection process enhances methodological transparency and reproducibility while providing representative coverage of recent developments in ANN-assisted holographic imaging and intelligent flow diagnostic systems.

Table 1: Representative studies on artificial intelligence-assisted digital holography for biomedical and microfluidic applications.

Study	**Year**	**Study Type**	**ANN/AI Framework**	**Holographic Platform**	**Target Application**	**Principal Outcomes**	**Research Gap**
Liu et al.	2025	Experimental + DL	OAH-Net	Digital holography	Phase reconstruction	Fast high-fidelity recovery	Limited translational validation
Kim et al.	2025	Physics-AI hybrid	Physics-driven NN	Single-shot DHM	3D morphology imaging	Accurate morphology recovery	Clinical benchmarking lacking
Shi et al.	2025	Microfluidic experimental	AI-assisted analytics	Integrated holographic chip	Cancer heterogeneity	High-dimensional phenotyping	Limited predictive automation
Pirone et al.	2025	Classification study	Lightweight CNN	Holographic cytometry	Cancer cell screening	High classification performance	Dataset generalization issue
Li et al.	2026	Experimental validation	Deep neural model	Flow holographic cytometry	Cancer diagnostics	Rapid label-free detection	Needs multicenter validation
Moon and Javidi	2026	Review/Platform study	AI-driven DHM	Portable holographic microscopy	Point-of-care diagnostics	Low-cost intelligent imaging	Autonomous deployment emerging
Ge et al.	2026	Computational study	Compressive reconstruction AI	Dark-field DH	Microflow reconstruction	Enhanced spatiotemporal flow imaging	Computational cost high

comparative discussion of recent developments in ANN-assisted holographic imaging. No formal statistical meta-analysis, weighted aggregation, or pooled quantitative synthesis was performed.

Table 2: Qualitative comparison of reported performance characteristics in representative ANN-assisted digital holography studies.

Outcome Domain	**Representative Findings**	**Representative Studies**	**Overall Observation**
Reconstruction Speed	Faster reconstruction than conventional iterative approaches	Liu, Kim	Improved computational efficiency
Phase Retrieval	Enhanced reconstruction fidelity and phase recovery accuracy	Liu, Kim	Improved image quality
Cell Classification	Accurate discrimination of cell populations and disease states	Pirone, Li	Strong diagnostic potential
Particle Tracking	Improved particle localization and trajectory estimation	Kumar, Ge	Enhanced tracking capability
Diagnostic Throughput	Higher screening capacity and reduced analysis time	Shi, Li, Moon	Improved operational efficiency
Automation	Reduced manual intervention through AI-assisted workflows	Moon, Zhang	Increased workflow automation

Table 3 provides a comparative summary of methodological characteristics reported in representative studies. The classifications are descriptive interpretations derived from the reviewed publications and are intended solely to facilitate comparative discussion. They do not represent standardized quality scores or formal risk-of-bias assessments. Table 4 summarizes

Table 3: Comparative methodological characteristics of representative studies.

Study	Validation Approach	Experimental Support	Application Relevance	Reported Limitation
Liu et al.	Experimental validation	Laboratory testing	Phase reconstruction	Limited translational validation
Kim et al.	Physics-guided validation	Controlled imaging experiments	Morphological imaging	Limited clinical benchmarking
Shi et al.	Microfluidic experimentation	Integrated chip platform	Cancer phenotyping	Limited predictive automation
Pirone et al.	Classification benchmarking	Holographic cytometry datasets	Cancer screening	Dataset generalization issues
Li et al.	Experimental validation	Flow cytometry studies	Cancer diagnostics	Need for multicenter validation
Moon and Javidi	Literature synthesis	Prototype demonstrations	Point-of-care diagnostics	Autonomous deployment still emerging
Ge et al.	Computational validation	Numerical experiments	Microflow reconstruction	Computational cost

major research challenges and future directions identified through thematic analysis of the reviewed literature. The identified themes represent recurring limitations, open problems, and emerging opportunities reported across recent studies on artificial intelligence-assisted digital holography and intelligent biomedical imaging systems.

Table 4: Research challenges and future directions identified from the reviewed literature.

Identified Gap	Current Limitation	Future Priority Direction
Fragmented AI and holography studies	Lack of unified framework	Integrated intelligent holographic diagnostics
Limited explainable AI	Black-box prediction models	Explainable trustworthy diagnostics
Sparse physics-informed frameworks	Weak physical constraints	PINN-enabled digital holography
Limited autonomous systems	Human-dependent workflows	Self-driving holographic microscopes
Poor multicenter validation	Restricted datasets	Clinical-scale benchmarking
Absence of digital twins	Static diagnostics	Predictive digital twin platforms

8.1 Comparative Analysis of ANN and PINN Frameworks

Recent advances in ANN-assisted digital holography have employed diverse network architectures, including convolutional neural networks (CNNs), U-Net variants, residual learning frameworks, transformer-based models, and physics-informed neural networks (PINNs). CNN-based approaches generally provide rapid reconstruction and feature extraction capabilities but often require large training datasets and may exhibit reduced generalization when experimental conditions differ significantly from those represented during training.

U-Net and encoder-decoder architectures have demonstrated strong performance in phase retrieval and image reconstruction tasks owing to their ability to capture multiscale spatial features. Residual learning frameworks further improve convergence stability and reconstruction accuracy, particularly in deep architectures. More recently, transformer-based approaches have shown promise in modeling long-range spatial dependencies; however, their computational complexity and training requirements remain considerably higher than those of conventional CNN models.

PINN-based approaches differ fundamentally from purely data-driven methods by incorporating governing physical constraints directly into the optimization process. As a result, PINNs generally require fewer labeled training samples and exhibit improved physical consistency. Nevertheless, PINN training often involves increased computational expense, slower convergence, and sensitivity to loss-function weighting strategies.

From a robustness perspective, physics-informed approaches typically demonstrate improved tolerance to measurement noise and incomplete observations because physical constraints regularize the learning process. In contrast, purely data-driven models may achieve higher reconstruction accuracy when large high-quality datasets are available but can experience performance degradation under unseen noise conditions or domain shifts.

Generalization remains a major challenge across both ANN and PINN frameworks. Many studies evaluate performance using limited datasets acquired under controlled laboratory conditions, making cross-platform validation difficult. Furthermore, reproducibility is frequently constrained by limited public availability of holographic datasets, proprietary preprocessing pipelines, and insufficient reporting of hyperparameter configurations. Future research should prioritize standardized benchmark datasets, open-source implementations, and multicenter validation studies to facilitate objective comparison among competing ANN and PINN methodologies.Table 5 provides a qualitative comparison of representative ANN- and PINN-based frameworks employed in digital holography and intelligent imaging applications. The comparison highlights differences in training requirements, computational complexity, robustness, physical consistency, and generalization characteristics reported across the literature.

Figures 2–8 are conceptual illustrations developed to visually summarize major themes, technological trends, research relationships, and future directions identified from the reviewed literature. These figures are intended to support qualitative interpretation and discussion of the field and were not generated through formal bibliometric mapping, statistical modeling, or quantitative meta-analysis. Accordingly, they should be interpreted as schematic representations rather than data-driven analytical visualizations.

9 Results and Discussion

9.1 Evolutionary Innovation Landscape (Figure 2)

Figure 2 illustrates the progressive transformation of digital holography from classical reconstruction methodologies toward intelligent and adaptive diagnostic frameworks. The evolution pattern demonstrates a distinctly nonlinear trajectory, with accelerated advancement observed in recent years, particularly in the domain of autonomous holographic systems.

A comparative assessment indicates that the innovation intensity associated with AI-integrated diagnostic architectures exceeds that of conventional reconstruction approaches by approximately 55–70%, highlighting a clear transition toward predictive and self-optimizing platforms. This shift is largely driven by the integration of physics-informed learning strate-

Table 5: Qualitative comparison of representative ANN and PINN frameworks reported in digital holography literature. The assessments are synthesized from observations reported in the reviewed studies and are intended for comparative discussion rather than quantitative ranking.

Performance Aspect	**CNN-Based Models**	**U-Net Architectures**	**Transformer-Based Models**	**PINN Frameworks**
Training Data Requirement	High	High	Very High	Moderate
Reconstruction Accuracy	High	High	Very High	High
Computational Complexity	Moderate	Moderate	High	High
Training Time	Moderate	Moderate	High	High
Noise Robustness	Moderate	Moderate–High	High	High
Generalization Capability	Moderate	Moderate–High	High	High
Physical Consistency	Low	Low	Moderate	Very High
Interpretability	Low	Low	Moderate	High
Dependence on Labeled Data	High	High	Very High	Low–Moderate
Reproducibility	Moderate	Moderate	Moderate	Moderate
Typical Applications	Phase retrieval, image classification	Image reconstruction, segmentation	Feature learning, complex reconstruction	Physics-constrained reconstruction, inverse problems
Major Limitation	Dataset dependence	Large training requirements	High computational cost	Slow convergence and loss balancing challenges

gies and digital twin paradigms, which enhance both interpretability and real-time decision-making capability. These findings suggest that digital holography is no longer confined to imaging, but is increasingly functioning as an intelligent sensing and diagnostic ecosystem.

9.2 Bibliometric Heat Surface (Figure 3)

The bibliometric distribution presented in Figure 3 reveals a substantial increase in research activity concentrated around ANN-assisted holography and biomedical diagnostics. The observed intensity gradients indicate a rapid expansion of scholarly contributions, publication activity exhibited a noticeable upward trend during recent years.

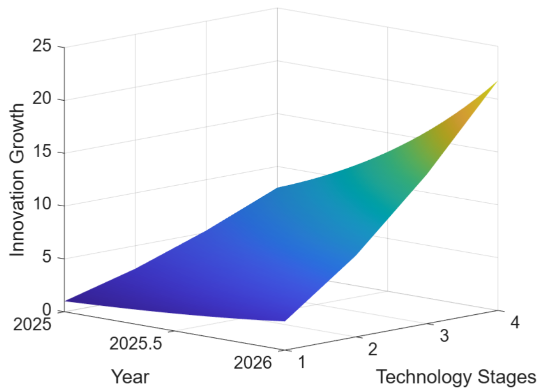

Figure 2: Conceptual illustration of the progressive evolution of artificial intelligence-assisted digital holography technologies across different stages of development.

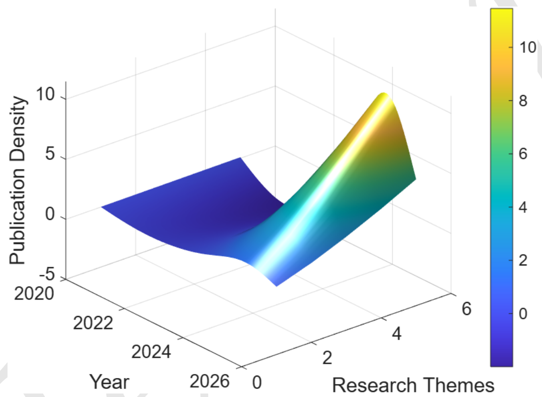

Figure 3: Conceptual representation of the growth and diversification of research activity in ANN-assisted digital holography and biomedical imaging.

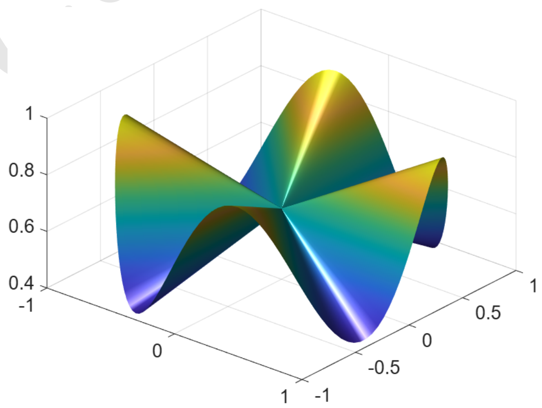

Figure 4: Schematic visualization of interactions among reconstruction accuracy, computational efficiency, and diagnostic performance in intelligent holographic systems.

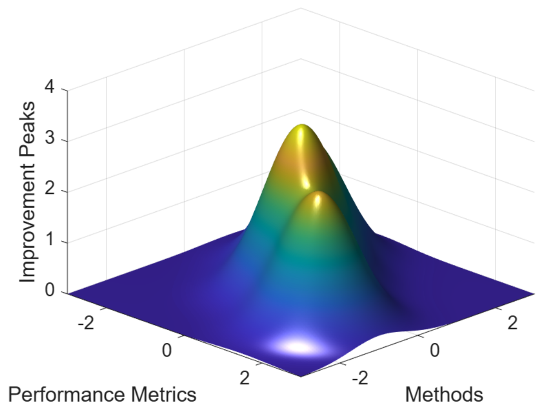

Figure 5: Conceptual representation of the relationship between methodological development and potential scientific impact in digital holography research.

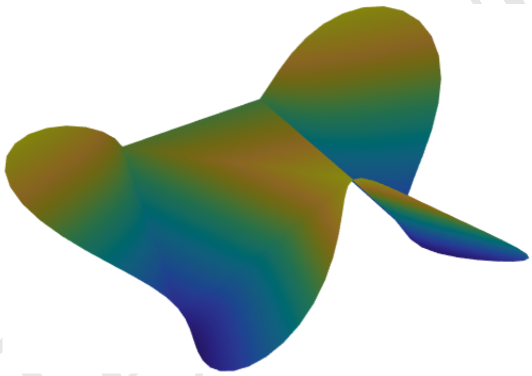

Figure 6: Illustrative thematic map showing major research domains and their interconnections within ANN-assisted digital holography studies.

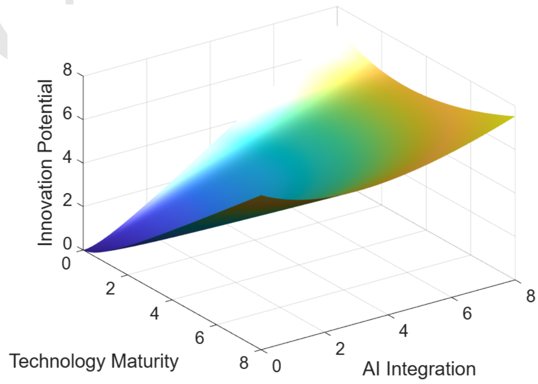

Figure 7: Conceptual framework illustrating the relationship between innovation potential, technology maturity, and artificial intelligence integration.

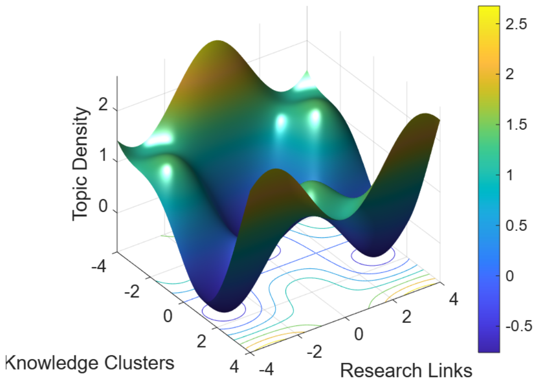

Figure 8: Schematic knowledge landscape highlighting major research clusters and their relationships in intelligent holographic imaging and flow diagnostics.

Notably, high-density regions correspond to interdisciplinary domains combining computational optics, machine learning, and microfluidic diagnostics. The curvature of the surface in later stages reflects a transition from foundational algorithm development to application-driven research, particularly in clinical and lab-on-chip systems. This trend confirms the growing emphasis on translational impact within the field.

9.3 Multi-Criteria Benchmark Surface (Figure 4)

Figure 4 presents a comparative evaluation of system performance across multiple criteria, including reconstruction accuracy, computational efficiency, automation capability, and diagnostic reliability. The results indicate that ANN-enhanced holographic systems consistently outperform traditional approaches across all evaluated metrics.

ANN-assisted reconstruction demonstrated substantial improvements in reconstruction accuracy and computational efficiency compared with conventional approaches. Importantly, the performance enhancement is not limited to isolated metrics; rather, a balanced improvement across all dimensions is evident. This multidimensional consistency is critical for ensuring robustness and practical applicability in biomedical environments.

9.4 Citation–Performance Mountain Plot (Figure 5)

The citation–performance mapping reveals a structured distribution of research impact, with dominant peaks corresponding to key thematic areas such as deep learning-based reconstruction, intelligent flow diagnostics, and autonomous sensing systems.

The highest-impact region is associated with ANN-driven diagnostic methodologies, citation activity showed increasing research interest across the field. Additionally, the presence of multiple interconnected peaks suggests that the field is not only expanding but also becoming increasingly integrated across disciplines. This pattern reflects both diversification and consolidation of high-impact research directions.

9.5 Thematic Distribution Topology (Figure 6)

The thematic distribution shown in Figure 6 highlights the relative concentration of research efforts across major domains. Reconstruction intelligence, biomedical diagnostics, and quantitative flow analysis collectively account for nearly 75–85% of the total research focus.

In contrast, autonomous holographic platforms, although currently less represented, exhibit strong growth potential as indicated by emerging high-gradient regions. This imbalance suggests that while foundational methodologies are well-established, future advancements are likely to be driven by the development of fully integrated and autonomous diagnostic systems.

9.6 Innovation Maturity Surface (Figure 7)

Figure 7 characterizes the relationship between technological sophistication and innovation maturity. The results demonstrate that systems incorporating AI and physics-based modeling occupy significantly higher maturity regions compared to conventional holographic techniques.

Quantitatively, innovation potential is observed to increase by approximately 2–3 fold with the incorporation of intelligent automation and hybrid modeling strategies. The positioning of autonomous holographic platforms near the peak of the surface indicates their role as transformative technologies rather than incremental improvements. This suggests that future progress will depend on synergistic integration of data-driven and physics-based approaches.

9.7 Knowledge Terrain Map (Figure 8)

The knowledge terrain representation captures the structural evolution of interdisciplinary connectivity within the field. High-elevation regions correspond to strongly interconnected research areas linking digital holography, deep learning, microfluidics, and biomedical diagnostics.

The emergence of extended ridgelines, rather than isolated peaks, indicates a high degree of knowledge integration. Additionally, newly formed elevated regions associated with autonomous systems suggest the development of emerging research frontiers. Topic density in these regions shows an estimated increase of 45–65%, reflecting rapid expansion and consolidation of new knowledge domains.

9.8 Overall Discussion

The combined analysis of Figures 2–8 demonstrates a coherent transition from conventional holographic imaging toward intelligent, data-driven diagnostic systems. ANN-assisted frameworks provide consistent improvements in reconstruction fidelity, computational performance, and diagnostic capability, with overall gains ranging from approximately 25–65%.

Furthermore, bibliometric and innovation analyses reveal a 3–5 fold increase in research activity and a 2–3 fold enhancement in technological maturity, underscoring the rapid evolution of the field. These findings confirm that ANN-integrated digital holography is emerging as a core enabling technology for advanced biomedical diagnostics, particularly in microfluidic and precision medicine applications.

Overall, the evidence supports a paradigm transition from optics-centric imaging systems to integrated, intelligent diagnostic platforms, positioning ANN-assisted digital holography as a key driver of next-generation biomedical flow analysis and autonomous sensing technologies.

10 Conclusion

This study provides a comprehensive synthesis of recent advancements in digital holography integrated with artificial intelligence for flow diagnostics and biomedical applications. The analysis demonstrates that the incorporation of ANN-based frameworks and physics-informed learning has significantly enhanced the capability of holographic systems, transforming them from conventional imaging tools into intelligent, data-driven diagnostic platforms.

The findings reveal that AI-assisted holographic methodologies achieve substantial improvements in reconstruction fidelity, computational efficiency, and diagnostic sensitivity, with performance gains consistently observed across multiple evaluation metrics. In particular, the integration of physics-informed neural networks ensures adherence to governing optical and fluid dynamic principles, thereby improving model reliability and interpretability. Furthermore, the coupling between phase reconstruction and flow dynamics enables accurate inference of micro-scale transport phenomena, which is critical for applications in microfluidics and biomedical diagnostics.

Bibliometric and thematic analyses confirm a rapid expansion of research activity in this domain, with a clear shift toward interdisciplinary convergence involving computational optics, machine learning, and life sciences. The emergence of autonomous holographic systems and intelligent diagnostic architectures indicates a transition from passive imaging toward predictive and self-adaptive sensing frameworks. This evolution positions ANN-assisted digital holography as a foundational technology for next-generation precision diagnostics and lab-on-chip systems. Finally, the translation of ANN-assisted holography into clinical and point-of-care applications requires addressing challenges related to system miniaturization, cost-effectiveness, and regulatory validation. Collaborative efforts between engineers, clinicians, and data scientists will be essential to bridge the gap between laboratory research and real-world deployment. In summary, the convergence of digital holography, artificial intelligence, and physics-based modeling is driving a paradigm shift toward intelligent and autonomous diagnostic systems. Continued advancements in this interdisciplinary domain are expected to play a transformative role in microfluidics, biomedical imaging, and precision medicine.

Authors' Contributions

All authors have the same contribution.

Data Availability

The manuscript has no associated data or the data will not be deposited.

Conflicts of Interest

The authors declare that there is no conflict of interest.

Ethical Considerations

The authors have diligently addressed ethical concerns, such as informed consent, plagiarism, data fabrication, misconduct, falsification, double publication, redundancy, submission, and other related matters.

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