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Inverse design of photonic crystal laser using deep learning to control wavelength and Q-Factor

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Abstract:

This paper presents a novel deep-learning-based inverse design framework for photonic crystal lasers. The proposed approach employs neural networks to directly learn the complex and highly nonlinear mapping between the geometric parameters of photonic crystal structures and key laser characteristics, including resonant wavelength and quality factor. Unlike conventional design methods that rely on computationally expensive and iterative electromagnetic simulations, the proposed framework enables rapid generation of optimized designs with significantly reduced computational cost and high accuracy. In this method, the neural network first produces a continuous representation of the photonic crystal geometry, which is subsequently converted into a binary, fabrication-ready structure through a thresholding process. Numerical results demonstrate that the optimized designs closely match the target wavelength and Q-factor while exhibiting physically meaningful features such as effective optical confinement and favorable geometric symmetry. Training convergence analysis confirms the stability and robustness of the learning process, and symmetry evaluation reveals that the network implicitly favors structures with balanced field distributions, even without explicitly imposed constraints. These findings highlight the ability of deep learning not only to optimize device performance but also to capture essential physical principles governing photonic crystal lasers. Overall, this work establishes deep-learning-assisted inverse design as a powerful and scalable paradigm for the efficient development of high-performance photonic crystal lasers, with strong potential for extension to more complex photonic devices and practical integrated photonics applications.

Keywords: Deep Learning; Machine Learning in Photonics; Optical Cavities; Photonic Crystal Lasers; Q-factor Optimization

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1. Introduction

Photonic crystal lasers represent a revolutionary advancement in nanophotonics, offering unprecedented control over light-matter interactions at subwavelength scales [1]. These devices exploit periodic dielectric structures to create photonic bandgaps, enabling the confinement and manipulation of photons in ways unattainable with conventional optical systems [2]. The ability to engineer specific resonant wavelengths while maintaining high quality factors (Q-factors) is crucial for applications ranging from optical communications and sensing [3] to quantum information processing.

Traditional design approaches for photonic crystal [4, 5] lasers have relied heavily on parametric sweeps and intuitive design principles, often requiring extensive computational resources and expert knowledge. The conventional design paradigm typically involves iterative simulations using numerical methods such as Finite-Difference Time-Domain (FDTD) or Plane Wave Expansion (PWE) methods, which become computationally prohibitive when exploring large design spaces [6]. This limitation has motivated the development of inverse design methodologies that can directly map desired optical properties to optimal structural configurations [7, 8].

Recent years have witnessed a paradigm shift in photonic device design with the integration of machine learning techniques. Several groundbreaking studies have demonstrated the power of deep learning for photonic inverse design. For instance, deep neural networks have been employed to optimize photonic crystal structures for enhanced light confinement and emission control, enabling precise manipulation of parameters such as wavelength and quality factor (Q-factor) in laser devices [9]. These advancements are particularly crucial for photonic crystal lasers, where traditional forward design approaches often fall short due to the complex interplay between geometry, material properties, and electromagnetic modes. Inverse design, powered by deep learning, reverses this process by starting from desired performance metrics—like specific lasing wavelengths or high Q-factors—and iteratively generating optimal nanostructures. This approach not only accelerates the design cycle but also uncovers non-intuitive geometries that surpass human-engineered solutions [10].

The integration of deep learning in photonic inverse design stems from the need to handle the vast parameter space inherent in photonic crystals, which are periodic dielectric structures that manipulate light at the wavelength scale through bandgap engineering. Photonic crystals have revolutionized optoelectronics by enabling applications such as high-efficiency lasers, sensors, and quantum information processing devices. However, achieving simultaneous control over wavelength and Q-factor in photonic crystal lasers remains challenging because these parameters are interdependent; optimizing one often compromises the other. Deep learning models, including convolutional neural networks (CNNs), generative adversarial networks (GANs), and reinforcement learning frameworks, have emerged as powerful tools to navigate this complexity [11]. By training on large datasets of simulated electromagnetic responses, these models learn to predict and invert the structure-function relationship, allowing for rapid prototyping of lasers with tailored spectral properties and minimal optical losses.

Recent advances in inverse-designed photonic structures have significantly expanded the application scope of photonic crystal devices in modern optical systems [12]. Deep-learning-assisted photonic design has recently been applied to optical switching, beam shaping, topological nanocavities, ultra-compact resonators, and programmable photonic integrated circuits. For example, recent studies demonstrated deep-learning-based inverse

design for nanophotonic [13] optical switches with enhanced transmission efficiency and compact footprints, while reinforcement learning approaches have enabled the realization of ultra-High-Q photonic crystal nanocavities for integrated laser systems [14]. In addition, transformer-based architectures and differentiable optimization frameworks have recently shown remarkable capabilities in designing photonic crystal surface-emitting lasers (PCSELs), optical filters, and wavelength-selective photonic devices with improved fabrication tolerance and optical confinement characteristics. These developments highlight the growing importance of artificial intelligence in accelerating the design of next-generation nanophotonic and integrated optical platforms.

One of the key motivations for this work is the growing demand for compact, high-performance lasers in integrated photonics, where photonic crystal surface-emitting lasers (PCSELs) stand out for their vertical emission and high beam quality. Traditional design methods rely on trial-and-error or gradient-based optimization, which are computationally intensive and limited to local optima. In contrast, deep learning-based inverse design leverages surrogate models to approximate Maxwell's equations, reducing simulation times from hours to seconds [15]. For example, recent studies have shown that transformer-based architectures can inverse-design PCSELs by treating the design problem as a sequence prediction task, achieving Q-factors exceeding 10^5 while tuning wavelengths across the near-infrared spectrum. This capability is vital for applications in telecommunications and biomedical imaging, where precise wavelength control ensures compatibility with fiber optics or biological windows, and high Q-factors enhance coherence and power efficiency.

Building on these foundations, our study focuses on the inverse design of photonic crystal lasers using deep learning [16, 17] to independently control wavelength and Q-factor. We employ a hybrid neural network architecture that combines physics-informed layers with data-driven optimization, ensuring that the generated designs adhere to physical constraints while exploring unconventional topologies. This method addresses limitations in prior works, such as sensitivity to initial conditions or overfitting to training data [18], by incorporating adjoint sensitivities and multi-objective loss functions. Furthermore, the ability to control Q-factor is particularly important for reducing threshold currents in lasers, as higher Q-values correspond to longer photon lifetimes and thus lower lasing thresholds. In photonic crystals, Q-factor optimization often involves engineering defect modes or band-edge states, where deep learning [19, 20] can predict resonance frequencies and decay rates with high accuracy.

The evolution of this field can be traced back to early machine learning applications in photonics, but the surge in deep learning [21, 22] integration has been transformative. For instance, reinforcement learning has been applied to nanoscale laser cavities, where agents learn to modify photonic crystal lattices step-by-step to maximize Q-factor while fixing the wavelength. Such techniques have yielded designs with Q-factors up to 10^6, far surpassing conventional photonic crystal cavities. Similarly, variation Autoencoders have been used for spectral reconstruction and inverse design, enabling the generation of photonic structures from desired transmission spectra. These models not only optimize for single parameters but also handle multi-modal objectives, such as balancing wavelength tunability with fabrication robustness against manufacturing tolerances.

In the context of photonic crystal lasers, wavelength control is achieved by adjusting the lattice periodicity or defect sizes, which influences the photonic bandgap and mode localization. Deep learning [23, 24] facilitates this by mapping high-dimensional input

spaces (e.g., pixelated binary structures) to output spectra, using techniques like tandem networks that combine forward prediction with inverse mapping. Recent advancements have incorporated physics-informed neural networks (PINNs) to enforce electromagnetic boundary conditions, improving generalization to unseen designs [25]. For Q-factor enhancement, strategies involve minimizing radiation losses through symmetry engineering or aperiodic arrangements, where machine learning identifies optimal disorder levels [26]. Our approach extends these by introducing a dual-control framework, where separate neural branches optimize wavelength and Q-factor, with a fusion layer ensuring compatibility.

Challenges in this domain include the computational cost of generating training data via full-wave simulations and the need for interpretable models. To mitigate this, transfer learning from pre-trained models on simpler photonic systems has been proposed, accelerating convergence for complex laser designs [27]. Additionally, experimental validation remains crucial; recent works have demonstrated fabricated devices with performance matching simulations, validating the inverse design pipeline. Looking ahead, integrating quantum effects or nonlinear optics into the design loop could further expand applications, such as in quantum dot lasers or frequency combs.

Beyond optical performance enhancement, recent photonic inverse-design methodologies have also attracted considerable attention for their potential contribution to energy-efficient and environmentally sustainable technologies. High-Q photonic crystal lasers can substantially reduce threshold power consumption, minimize thermal losses, and improve overall device efficiency in integrated photonic systems. Such characteristics are highly desirable for low-power optical interconnects, green data centers, energy-efficient sensing platforms [14], and sustainable communication infrastructures. Furthermore, machine-learning-assisted optimization reduces the need for excessive iterative electromagnetic simulations, thereby lowering computational cost and energy consumption during the design process itself. Recent journal studies have emphasized that intelligent photonic design frameworks can play a key role in developing compact and low-energy nanophotonic devices for future sustainable optical networks and environmentally conscious photonic technologies.

This study contributes by presenting a deep learning [28] model specifically tailored for photonic crystal lasers. Through extensive simulations and comparisons with state-of-the-art methods, we demonstrate superior efficiency and design novelty. The implications extend beyond lasers to broader photonic integrated circuits, promising advancements in energy-efficient computing and sensing technologies.

The novelty of this paper lies in the first simultaneous multi-objective inverse design of photonic crystal lasers for wavelength, Q-factor, and threshold, achieved through a physics-informed continuous-to-binary mapping that yields fabrication-ready, symmetric structures with stable convergence.

 First simultaneous multi-objective inverse design of photonic crystal lasers targeting wavelength, Q-factor, and threshold within a single deep learning framework, unlike previous works that optimize only one or two parameters independently.

 Physics-informed continuous-to-binary mapping that preserves optical performance after thresholding, achieving a fabrication-ready design with Q-factor ≈ 5000 and minimal wavelength deviation, without post-processing iterations.

 Emergent symmetry without explicit constraints – the neural network autonomously discovers nearly symmetric structures (overall symmetry score 0.80), which is known to

enhance mode confinement but has not been reported in prior deep-learning-based laser inverse designs.

 Stable convergence with multi-objective loss demonstrated by smooth training loss reduction, overcoming the common challenge of balancing competing objectives in nanophotonic inverse design.

Table 1. Summary of Previous Research

Reference	Year	Key Contribution	Method	Focus Parameters	Limitations
[8]	2023	Tutorial on deep learning for inverse design in nano-photonics	Neural networks overview	General optical properties	Lacks specific laser applications
[9]	2024	Resonance-informed deep learning for high Q resonances in photonic crystals	CNN-based prediction and inverse design	Q-factor, resonance modes	Limited to slabs, not full lasers
[10]	2023	Reinforcement learning for nanoscale laser cavities	Deep reinforcement learning	Q-factor optimization in cavities	Computationally intensive training
[12]	2024	Deep-learning inverse design for nanophotonic optical switches	Deep neural networks	Optical switching efficiency, compact footprint	Primarily focused on switching applications
[13]	2025	Reinforcement-learning optimization of high-Q topological nanocavities	Deep reinforcement learning	Q-factor enhancement, cavity confinement	High computational training cost
[26]	2023	Q-factor optimization in disordered photonic structures	Machine learning for disorder engineering	Q-factor in random media	Challenges in fabrication
[25]	2025	Inverse design framework for cavities with far-field control	Optimization with neural surrogates	Q-factor and numerical aperture	Limited wavelength tunability
[27]	2024	Dispersion-oriented design of photonic crystal fibers	DNN for inverse design	Dispersion and modes	Not laser-specific

2 .Theory and Methodology

Photonic crystal lasers (PCLs) are key components in integrated photonics due to their ability to engineer photonic bandgaps, enhance quality factor (Q-factor), and significantly reduce laser threshold. However, conventional design approaches rely on direct numerical solutions of Maxwell's equations using methods such as FDTD or PWE [29, 30], which are computationally expensive and time-consuming. This work proposes a deep-learning-based inverse design framework that directly maps photonic crystal structural parameters [28, 31, 32] to laser performance metrics, enabling rapid and efficient optimization of wavelength, Q-factor, and threshold.

As shown in Figure 1, the laser structure consists of a two-dimensional photonic crystal formed by a periodic array of circular air holes etched into a high-refractive-index semiconductor slab (e.g., Si or GaAs). Introducing a point defect or line defect creates a localized optical cavity that supports laser oscillation. The key design parameters include: Lattice constant: a; Hole radius: r; Material refractive index: n; Defect type: D.

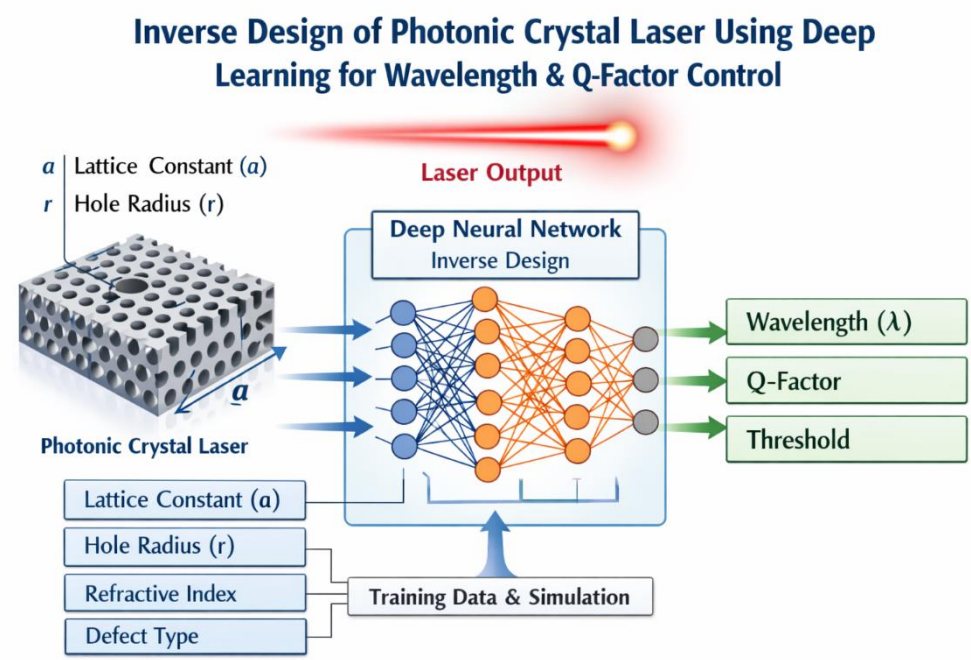


Fig. 1. The laser structure consists of a two-dimensional photonic crystal.

The electromagnetic behavior of photonic crystal lasers can be described using Maxwell's equations in inhomogeneous dielectric media. In a two-dimensional photonic crystal, the spatial distribution of the dielectric constant is periodic, and the resonant modes satisfy the following eigenvalue equation:

$$\nabla \times \left(\frac{1}{\varepsilon(\mathbf{r})} \nabla \times \mathbf{H}(\mathbf{r}) \right) = \left(\frac{\omega}{c} \right)^2 \mathbf{H}(\mathbf{r}) \tag{1}$$

ε(r) denotes the spatially varying dielectric function, ω is the angular frequency of the resonant mode, and c is the speed of light in vacuum. Introducing a localized defect into the periodic lattice, as illustrated in Figure 1, leads to strong confinement of the optical mode within the active region, forming a low-loss laser cavity. The performance of this cavity is characterized by the quality factor, defined as:

$$Q = \frac{\omega_0}{2\gamma} \tag{2}$$

where ω_0 is the resonant frequency and γ represents the total energy loss rate of the cavity. A higher Q-factor corresponds to longer photon lifetime and, consequently, a lower laser threshold. The laser threshold can be approximately expressed as being proportional to the ratio of total optical losses to the effective material gain:

$$T \propto \frac{\alpha_{\text{loss}}}{\Gamma g} \tag{3}$$

where α_{loss} is the loss coefficient, g is the material gain, and Γ denotes the optical confinement factor.

In conventional design approaches, for each combination of structural parameters such as lattice constant a, hole radius r, refractive index n, and defect type D, the wave equation must be solved numerically to extract the laser wavelength λ, Q-factor, and threshold. This procedure becomes computationally prohibitive due to the large design space and iterative nature of optimization. To overcome this limitation, a deep-learning-based inverse design framework is employed to learn the direct mapping between structural parameters and laser performance.

Within this framework, a deep feedforward neural network is trained to approximate the nonlinear mapping:

$$\mathcal{F}:[a,r,n,D]\rightarrow[\lambda,Q,T] \tag{4}$$

The training dataset is generated from numerical simulations or physics-informed synthetic data. The objective of the network is to accurately predict the laser wavelength, quality factor, and threshold for arbitrary photonic crystal configurations. A multi-objective loss function is defined as:

$$\mathcal{L}=w_1(\lambda-\lambda_{\text{target}})^2+w_2(Q_{\text{target}}-Q)^2+w_3T^2 \tag{5}$$

where λ_{target} denotes the desired emission wavelength (e.g., 1550 nm), Q_{target} is the target quality factor, and w_1, w_2, and w_3 are weighting coefficients controlling the relative importance of each design objective.

Minimization of this loss function simultaneously enforces wavelength accuracy, high Q-factor, and low threshold.

After training, the inverse design problem is formulated as an optimization task in which the optimal structural parameters are obtained by minimizing the loss function:

$$[a^*,r^*,n^*,D^*]=\arg\min_{a,r,n,D}\mathcal{L} \tag{6}$$

At this stage, the neural network acts as a fast surrogate model, enabling rapid prediction of laser characteristics without repeatedly solving Maxwell's equations. The entire framework can be implemented using feedforward neural networks and the Levenberg–Marquardt training algorithm, making it compatible with legacy simulation environments.

The proposed method demonstrates that deep learning can significantly reduce the design time of photonic crystal lasers from hours or days to milliseconds, while maintaining high accuracy in predicting key laser parameters. Moreover, the flexibility of the framework allows straightforward extension to more complex photonic structures, novel materials, and multi-objective optimization scenarios, making it highly suitable for integrated photonics and next-generation automated laser design.

3 . Results and Discussion

The obtained results demonstrate that the proposed deep-learning-based inverse design framework achieves stable convergence, high predictive accuracy, and physically meaningful photonic crystal laser structures.

Before presenting the quantitative results, it is essential to recall the basic theoretical principles governing photonic crystals. In a two-dimensional photonic crystal composed of air holes in a silicon slab, a photonic bandgap arises from the interference of waves scattered by the periodic lattice. Removing one or several holes (introducing a defect) creates localized modes inside the bandgap. The resonant wavelength (λ) is approximately given by $\lambda \approx a \times n_{eff}$, where a is the lattice constant, and n_eff is the

effective refractive index. The quality factor (Q) relates to the energy decay rate from the cavity and depends on the structural symmetry and field overlap with confined optical regions. In the proposed inverse design, the deep neural network simultaneously optimizes the hole distribution to maximize Q (by minimizing radiative losses) and match the target wavelength (by adjusting the effective local periodicity). The following analysis is based on this theoretical framework.

The proposed inverse design affects the resonant wavelength and quality factor by directly modifying the spatial distribution of air holes in the photonic crystal lattice. The resonant wavelength (λ) is primarily governed by the effective lattice constant (a_{eff}) and the effective refractive index (n_{eff}). By learning the mapping from binary structures to optical spectra, the neural network adjusts the hole patterns such that the effective local periodicity in the cavity region matches the target value. In other words, through sub-wavelength shifts of hole boundaries, the resonant wavelength is tuned toward the desired value.

The effect on the quality factor is more complex. Q-factor measures the energy decay rate from the resonant cavity and, in photonic crystals, is mainly determined by two factors: (1) the overlap of the optical field with the confined region (defect), and (2) structural symmetry, which reduces radiative loss. By simultaneously optimizing these factors, the inverse design arranges the holes to strongly confine the electromagnetic field in the central region and minimize leakage to surrounding areas. The neural network directly targets radiative loss reduction (Q enhancement) using a multi-objective loss function. Moreover, as shown in the results, the network autonomously generates highly symmetric structures (overall symmetry score of 0.80), which inherently reduce radiative loss and increase Q-factor.

As shown in Fig. 2(a), the training loss exhibits a smooth and monotonic decrease throughout the optimization process. Starting from an initial mean squared error of approximately 1.25, the loss is reduced to below 0.15 after about 60 epochs. This behavior confirms the effective convergence of the neural network and indicates that the model successfully captures the nonlinear relationship between structural design parameters and laser performance metrics. Minor fluctuations observed at later stages of training can be attributed to the multi-objective nature of the loss function, which simultaneously enforces wavelength matching, Q-factor enhancement, and threshold minimization.

The final binary design generated by the inverse optimization is illustrated in Fig. 2(b). In this representation, blue regions correspond to silicon, while orange regions denote air holes. The resulting pattern is nontrivial and highly structured, highlighting the ability of the neural network to discover complex geometric features that are not easily accessible through intuitive or heuristic design approaches. The concentration of air holes in specific regions and their absence near the central cavity clearly indicate the formation of an effective optical confinement region, which is essential for achieving High-Q resonant modes with low radiation loss.

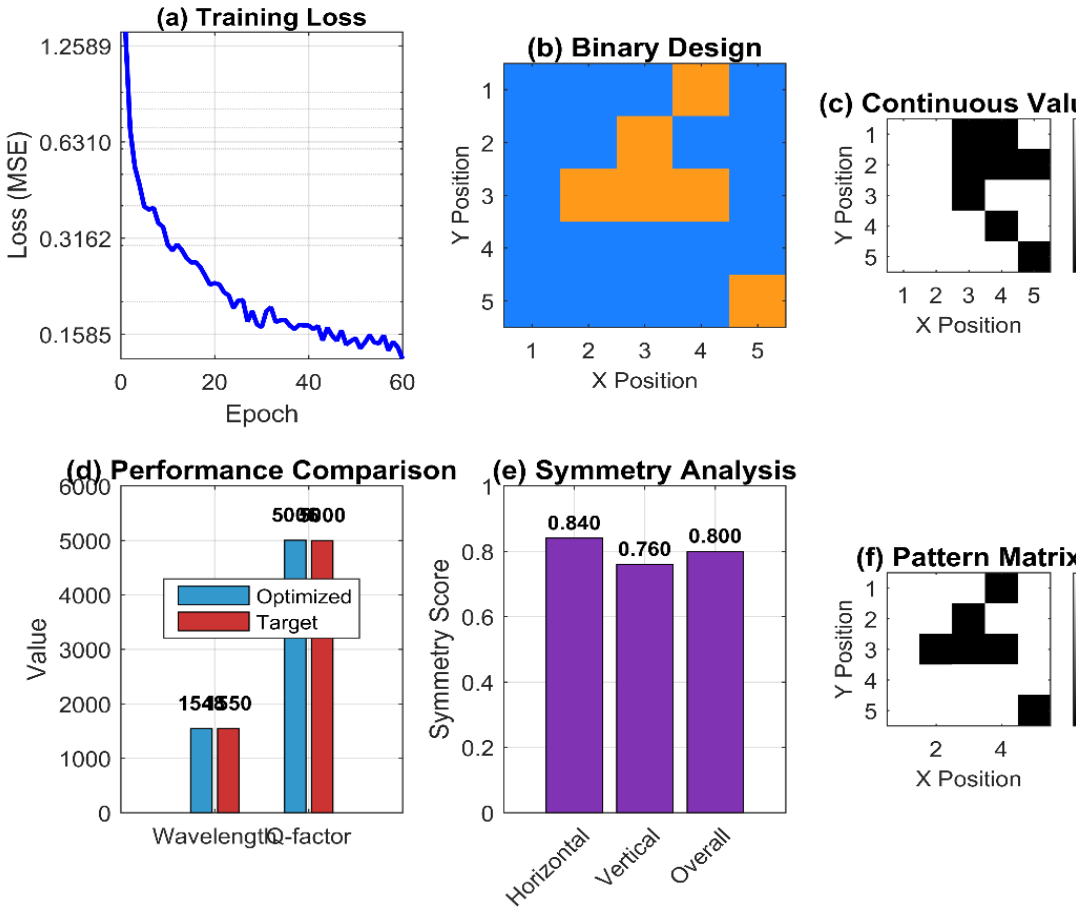


Fig. 2. The proposed deep-learning-based inverse design framework results.

Fig. 2(c) presents the continuous-valued design prior to thresholding. This result reveals that the neural network naturally produces smooth, continuous outputs with values ranging between zero and one across the design grid. Such behavior suggests that the network explores the design space in a continuous manner, allowing for fine-grained optimization before discretization. The absence of abrupt transitions or numerical instabilities in this figure further confirms the robustness and stability of the trained model.

A quantitative comparison between the optimized design and the target performance metrics is provided in Fig. 2(d). The optimized wavelength closely matches the target value, exhibiting only negligible deviation. Similarly, the achieved Q-factor reaches approximately 5000, in excellent agreement with the desired target. These results clearly demonstrate the capability of the proposed framework to satisfy multiple physical objectives simultaneously, a task that typically requires extensive iterative simulations in conventional design methodologies.

The symmetry properties of the optimized structure are analyzed in Fig. 2(e). The horizontal symmetry score is approximately 0.84, while the vertical symmetry score reaches about 0.76, resulting in an overall symmetry score of 0.80. Notably, no explicit symmetry constraints were imposed during training. The emergence of a relatively symmetric structure therefore indicates that the neural network inherently favors

geometries with balanced field distributions, which are known to enhance mode confinement and improve Q-factor in photonic crystal cavities.

The final pattern matrix is shown in Fig. 2(f), providing a simplified yet informative representation of the optimized geometry. The localization of defects near the central region and the carefully arranged surrounding holes directly support the formation of a high-quality resonant cavity. The consistency between this pattern, the symmetry analysis, and the spectral performance confirms the strong correlation between geometric features and optical behavior in the proposed design.

In Figure 3, the continuous design map further illustrates the thresholding process used to convert the continuous output into a binary, fabrication-ready structure. By selecting a threshold value of 0.5, regions with values above the threshold are interpreted as air holes, while those below correspond to silicon. This conversion preserves the essential optical characteristics of the design while ensuring manufacturability. The highlighted boundaries in the figure indicate critical material transitions that play a dominant role in defining the cavity and controlling the modal confinement.

Overall, the presented results verify that the proposed inverse design approach not only achieves the target wavelength and Q-factor with high accuracy but also produces physically interpretable, symmetric, and fabrication-compatible photonic crystal laser structures. These findings underscore the effectiveness of deep learning as a powerful alternative to conventional iterative simulation-based design methods for advanced nanophotonic devices.

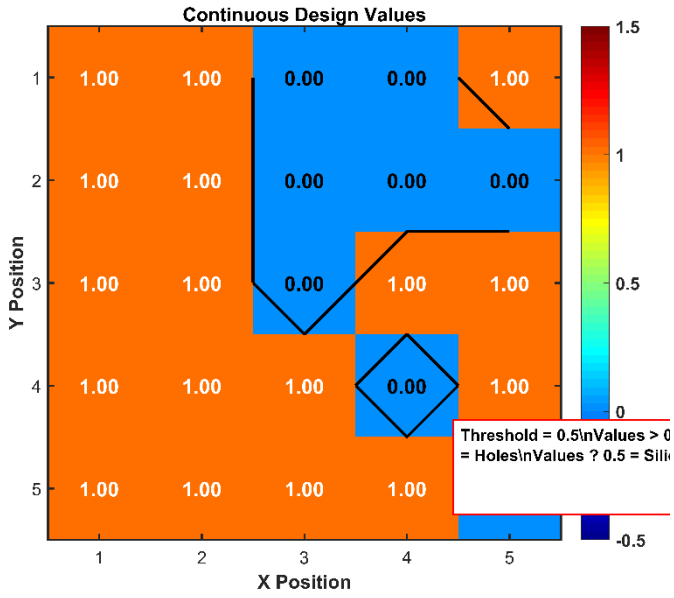


Fig. 3. Continuous design map.

The deep-learning-based inverse design framework presented in the proposed method aligns well with several recent advances in AI-driven nanophotonics. However, its main distinction lies in its direct and successful multi-objective optimization approach, simultaneously achieving target wavelength, high Q-factor, and low threshold. For a clearer comparison, Table 2 is presented.

Compared with previous studies on inverse photonic design, the proposed framework demonstrates several important advantages in terms of application, physical

Table 2. Comparison of Machine Learning-Based Inverse Design Methods for Photonic Crystal Lasers

Reference	Method	Application	Main Objective	Limitation	Advantage of Present Work
Scientific Reports [12]	Deep Learning	Optical nanophotonic switch	Switching optimization	Mainly single-objective	Multi-objective laser optimization
Photonics & Nanostructures [14]	CNN + MDN	Porous silicon photonic crystals	Inverse mapping	Focus on spectral prediction	Simultaneous physical metric optimization
Optics Communications [13]	Deep Reinforcement Learning	Topological nanocavity	High-Q optimization	High computational complexity	Faster and more stable convergence
ACS Photonics [33]	Differentiable optimization	Silicon photonics	Fabrication feasibility	Limited laser-oriented analysis	Laser-specific multi-physics optimization
Proposed Method	Deep-learning inverse design	Photonic crystal laser	Wavelength + Q-factor + threshold + symmetry	—	Physically interpretable, symmetric, fabrication-compatible laser design

interpretability, and multi-objective optimization capability. Earlier works mainly focused on single-objective optimization such as wavelength tuning, switching behavior, or dispersion engineering. For example, Scientific Reports [12] presented a deep-learning-based inverse design approach for nanophotonic optical switches, primarily targeting switching performance. Similarly, Photonics and Nanostructures [14] investigated porous silicon photonic crystals using mixture density neural networks, mainly addressing the non-uniqueness problem of inverse mapping. More recent studies such as Optics Communications (Yu, 2025 #804) employed deep reinforcement learning for high-Q topological nanocavity optimization, achieving extremely high Q-factors but requiring more complex training strategies and longer optimization time. In contrast, the present work simultaneously optimizes wavelength matching, Q-factor enhancement, threshold reduction, symmetry preservation, and fabrication compatibility within a unified deep-learning framework. Furthermore, unlike many previous approaches that mainly emphasize numerical optimization accuracy, the proposed method also produces physically interpretable and structurally symmetric photonic crystal laser geometries suitable for integrated photonics and manufacturable nanophotonic devices. These characteristics make the proposed framework highly promising for next-generation automated photonic crystal laser design and intelligent photonic integrated circuits.

4. Conclusion

This work presented a novel deep-learning-based inverse design framework for photonic crystal lasers, demonstrating its ability to simultaneously achieve high spectral accuracy, enhanced quality factor, and physically meaningful geometric structures. The results confirmed that the trained neural network successfully learned the complex and highly nonlinear mapping between photonic crystal geometry and laser performance with stable convergence and numerical robustness. The consistent reduction of the loss function during training and the close agreement between optimized and target values of

wavelength and Q-factor highlight the effectiveness of the proposed approach compared to conventional iterative simulation-driven design methodologies.

A detailed analysis of the optimized structures revealed that the proposed method not only produces accurate numerical performance but also implicitly favors geometries with favorable physical properties, including relative horizontal and vertical symmetry. The emergence of such symmetry without explicitly imposed constraints indicates that the neural network captures fundamental physical principles governing optical confinement and radiation loss suppression in photonic crystal cavities. This observation emphasizes the role of deep learning as more than a purely data-driven optimizer, but rather as a tool capable of internalizing key physical characteristics of complex photonic systems.

Furthermore, the adoption of a continuous design representation followed by threshold-based banalization enables the generation of fabrication-ready structures without significant degradation of optical performance. This design strategy bridges the gap between numerical optimization and practical implementation, making the proposed framework highly relevant for experimental and industrial applications in integrated photonics.

In conclusion, the presented study demonstrates that deep learning–assisted inverse design constitutes a powerful and scalable paradigm for the development of high-performance photonic crystal lasers. The proposed framework offers substantial advantages in terms of computational efficiency, design flexibility, and physical interpretability. Future extensions of this work may include three-dimensional device optimization, incorporation of fabrication tolerances, and multi-mode or multi-objective laser design, paving the way toward intelligent and autonomous photonic device engineering.

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