

Chapter 1

Research Background and Progress

Abstract This chapter will briefly introduce the research background of Optical Neural Networks (ONNs), while also reviewing the developmental trajectory of ONNs. As a novel computing paradigm, ONNs possess inherent advantages such as low latency, low power consumption, and ultra-fast parallel signal processing compared to electronic neural networks. Although ONNs experienced slow development in the past due to limitations in fabrication technology, societal demands, and data resources, recent advancements in these areas have facilitated rapid progress in ONNs. This chapter will provide a detailed overview of the current research status of ONNs, analyze potential areas for improvement in different types of ONN studies, and present the research content, significance, and objectives to be explored in this thesis.

1.1 Introduction

Over the past two decades, the rapid development of semiconductor process technology [1] and the continuous optimization and improvement of computing hardware architectures, including GPUs, FPGAs, and ASICs [2–8], have made computing resources increasingly abundant. Driven by the vast computing resources, neural networks have achieved widespread application and remarkable progress across diverse domains [2–8], such as computer vision [9], natural language processing [10], speech recognition [11], autonomous driving [12], and biomedical sciences [13–15]. Nevertheless, as the appetite for intelligent solutions grows, the complexity of tasks that neural networks are expected to manage has escalated correspondingly, leading to a rapid surge in computing resource consumption, especially when tackling intricate tasks. By 2020, the precision of the semiconductor process had approached 3 nm [1], which is approaching the physical limit of transistors. Concurrently, the field of artificial intelligence is evolving at a breakneck pace, with its hunger for computing resources intensifying daily. In the future, as neural networks face even

more complex challenges, the escalating demand for computing resources is anticipated to encounter a significant bottleneck. Therefore, a new computing paradigm is urgently needed to address and surmount this looming constraint.

In 1989, H. John Caulfield et al. systematically introduced optical neural networks (ONNs) [16]. They indicated that the mutual penetration of traditional optical information processing and neural network knowledge systems created ONNs and believed that, in certain specific cases, ONNs would have more significant advantages than electronic neural networks. At that juncture, ONNs were predominantly constructed with discrete optical elements, which limited their applicability. Moreover, the specific conditions, such as the absence of the current societal demand for substantial computing resources, the nascent stage of neural network algorithms and applications, and the underdevelopment of advanced optical components essential for ONNs, resulted in sluggish progress in ONN research for a considerable period. Until recently, the emergence of massive data and the flourishing development of machine learning algorithms such as deep learning have provided beneficial conditions for advancing neural networks, making their applications in various industries more extensive and in-depth. At present, the artificial intelligence era is rising. Nonetheless, electronic computing hardware is encountering physical structure limitations that hinder further enhancements, leading to a predicament where it cannot furnish the greater computing resource support required by the burgeoning intelligent era. Thus, there is an urgent need to find a new computing paradigm to provide greater computing resource support. ONNs represent such a paradigm, offering numerous advantages over traditional electronic hardware computing architectures. For instance, ONNs exhibit exceptionally low energy consumption during inference calculations and benefit from their capacity to support high-speed parallel signal processing, resulting in faster processing speeds than their electronic counterparts. It is crucial to highlight that the enhancement of ONNs in task processing speed is not solely reliant on the miniaturization of device structures. Furthermore, the current state of semiconductor processing technology can fully meet the fabrication requirements for optical devices. Therefore, ONNs have received extensive attention and progress in recent years.

ONNs have several advantages over electronic neural networks, including low latency, low power consumption, and ultra-fast parallel signal processing. Neural networks need to process large matrix operations when performing inference tasks repeatedly, and the propagation of light is a natural matrix operation process. Consequently, light possesses an intrinsic advantage over traditional electronic hardware in executing large-scale linear matrix operations. The architecture of ONNs represents a novel computing paradigm that holds the potential to overcome the impending bottleneck in the upgrading of computing resources. Current research on ONNs primarily explores two domains: spatial bulk ONNs and silicon-based integrated ONNs. Among them, spatial bulk ONNs include free-space diffractive ONNs and other spatial bulk ONNs; silicon-based integrated ONNs include integrated interference ONNs, integrated wavelength-division ONNs, integrated diffractive ONNs, and other integrated ONNs. In the subsequent section, this thesis will provide a detailed overview of the research status of the ONNs mentioned above, analyze

the improvement space of current ONNs research work, and propose the research content, significance, and objectives of this thesis.

1.2 Research on Non-integrated ONNs

This section is structured into three parts to elucidate the current research status of non-integrated ONNs, encompassing free-space diffractive ONNs, lens-based ONNs, and other spatial bulk ONNs.

1.2.1 *Non-integrated Free-Space Diffractive ONNs*

Non-integrated free-space diffractive ONNs are primarily composed of individual optical components such as digital micromirror devices (DMD) [17], spatial light modulators (SLM) [17–20], and optical diffraction plates [21–29].

In 2018, Lin et al. [21] proposed a free-space diffractive optical neural network (DONN) based on diffraction theory and 3D printing technology. The team utilized the Rayleigh-Sommerfeld diffraction equation to express the propagation of the spatial light field analytically and pre-trained the structure parameters of the free-space DONN on a computer. Then, they adopted 3D printing technology to implement these parameters physically and subsequently completed the inference function of the free-space DONN in a physical hardware setup. The DONN achieved a 91.75% accuracy rate of blind testing on the MNIST dataset, and the inference calculation process was passive, significantly reducing system power consumption. The free-space DONN was achieved by designing the thickness of the diffractive structures at different positions on the diffraction plate to regulate the phase or amplitude changes of the light so that the incident light would produce interference as it propagated, thereby realizing the neural network's inference function. This implementation of the free-space DONN was non-reconfigurable and could only perform specific inference functions with a working wavelength of 0.75 mm. In 2019, Wu et al. [30] developed a metasurface operating in the visible light spectrum (at a wavelength of 700 nm) composed of rectangular prisms. The height of the rectangular prisms was fixed at 600 nm, while the spacing between adjacent rectangular prisms (i.e., the arrangement period) was fixed at 235 nm. The width of the rectangular prism varied from 50 to 180 nm, and the team achieved phase and amplitude control of each diffraction unit by changing the width of the rectangular prisms. This study conducted numerical simulations of free-space DONNs and theoretically validated their performance using the MNIST dataset. Additionally, the authors investigated the angle of incident light as it traveled to the metasurface and provided the phase and amplitude modulation of the unit cells under different incident angles. This work provides a comprehensive discussion of the incident angle, which is meaningful in guiding similar future works. In 2020, Qian et al. [22] engineered a free-space DONN based on diffraction theory

and mechanical processing technology that could perform optical logical operations. They demonstrated logical operations such as AND, OR, and NOT in an optical manner. The free-space DONN made by 3D printing or mechanical processing technologies, as in this work, has a larger working wavelength because a higher diffraction efficiency often requires the diffractive units to be of the same size as the working wavelength, and a larger working wavelength also requires a larger diffractive structure, making it easier to fabricate and process, such as the working wavelength of 17.6 mm in this work. In 2021, Zhou et al. [17] advanced significantly by developing a reconfigurable free-space DONN utilizing DMD and SLM. This innovation endowed free-space DONNs with reconfigurability and enhanced generality, broadening their applicability and computing efficiency. Despite these advancements, this work, along with similar studies, still encountered the following challenges: firstly, the physical bulk of such free-space DONNs often results in systems that are cumbersome and unstable, limiting their practicality; secondly, the alignment and calibration process between the individual optical components may introduce additional errors to the entire system.

The previously discussed free-space DONNs were composed of discrete optical components, and the calibration process between the individual components could lead to additional system errors, resulting in poor stability and portability. To address the calibration error problem between the individual components, Goi et al. [26] developed a highly integrated free-space DONN using double-photon nanolithography technology based on a complementary metal–oxide–semiconductor (CMOS) chip substrate. This approach involved creating multiple layers of diffractive metasurfaces, composed of subwavelength cylindrical arrays with a height variation step of 10 nm. This high level of integration facilitated the creation of approximately 500 million neurons per square centimeter, operating at a wavelength of 785 nm. In addition, Luo et al. [28] in 2022 engineered a multifunctional DONN consisting of metasurfaces based on a CMOS chip substrate, which could perform multi-channel sensing and multi-task processing in a visible light environment. This metasurface was composed of an array of nanopillars with subwavelength structures, where the height of the nanopillars was fixed at 600 nm, and the center spacing (i.e., the period) between adjacent nanopillars was 400 nm. The phase of propagating light could be modulated by changing the length and width of each nanopillar. This work utilized the polarization multiplexing scheme of subwavelength nanopillar structures to construct a multi-channel classifier framework. It achieved classification recognition for different tasks of MNIST and Fashion-MNIST. The integration density was approximately 6.25×10^6 neurons per square millimeter, and the operating wavelength was 532 nm. While the fabrication of metasurfaces with subwavelength structures on CMOS substrates for constructing free-space DONNs resolved the alignment and calibration issues associated with discrete optical components, it introduced significant processing challenges and costs. Moreover, achieving reconfigurability in such subwavelength structures across various metasurfaces remains a formidable challenge.

1.2.2 Non-integrated Lens-Based ONNs

Non-integrated lens-based ONNs are typically built up by a $4f$ lens group system [31–33]. In 2018, Chang et al. [31] used DMD as the signal input mechanism, placed a phase mask template in the Fourier plane of a $4f$ system (an optical system consisting of a set of optical lenses), and achieved the convolution operation function by modulating the Fourier plane spectrum. This implementation of the convolution function was characterized by near-zero energy consumption. When the camera captured the spectrum-modulated relevant information, it processed this data and executed the nonlinear operations in the electrical domain. This approach created a photoelectric hybrid neural network, or an electrically assisted ONN, where the roles of light and electricity were distinctly optimized: light handled the extensive linear matrix operations, while electricity managed the nonlinear calculations, which involved a relatively minor computational load. In 2019, Yan et al. [32] used the refractive properties of crystals to modulate image information in the Fourier plane or image plane to achieve deep free-space ONNs. This work introduced nonlinear correlation parameters of ferroelectric thin films [34, 35] into the numerical calculation process and introduced optical nonlinear functions at the end of each hidden layer during training. The performance of the free-space ONNs was compared and analyzed based on the training results with or without ferroelectric thin film nonlinear layers. In 2020, Miscuglio et al. [33] developed a large-scale parallel signal processing pure-amplitude free-space Fourier ONNs based on lens groups and DMDs, in which DMDs achieved the input and Fourier plane amplitude modulation. Therefore, the free-space Fourier ONNs based on the $4f$ system had reconfigurable capabilities, enhancing their computational versatility and broadening their potential applications.

1.2.3 Other Non-integrated Spatial Bulk ONNs

Other non-integrated spatial bulk ONNs [36–38] refer to neural networks composed of discrete optical components such as standard single-mode fibers, dispersion fibers, modulators, and band-pass filters. In 2021, Xu et al. [36] developed a photonic convolution accelerator utilizing the integrated optical frequency comb, the bulk electro-optic modulator (EOM), the standard single-mode optical fiber, and the photodetector (PD). Specifically, the EOM modulated the intensity at predetermined time slots across different wavelengths, and the PD detected the aggregate power of these wavelengths at specific times, thereby functionally realizing the equivalent operation of a convolution kernel. The operating speed of the photonic convolution kernel could reach tens of trillions of operations per second (11 TOPS), and the spatial bulk ONNs achieved an accuracy of 88% on the MNIST dataset in a blind test. In the same year, Stelzer et al. [37] constructed the computational function of a single neuron using a nonlinear device and multiple time-delay feedback loops. They engineered an

arbitrary-sized deep neural network by continuously reconstructing the parameters of the single neuron.

1.3 Research on Integrated ONNs

In Sect. 1.2, the non-integrated ONNs were introduced, which can be constructed with discrete optical components such as traditional lenses, DMDs, SLMs, and two-dimensional optical diffraction plates, or with diffraction plates on CMOS chip substrates, or with other discrete optical components such as dispersive optical fibers, modulators, and band-pass filters. Among these, discrete optical components have the disadvantages of large size, poor stability, and poor portability, which may introduce additional errors in the ONN system. The ONNs fabricated on CMOS chip substrates overcome the alignment and calibration issues between discrete components. However, the fabrication is difficult and costly, and it is challenging to realize subwavelength structures with reconfigurability between diffractive layers. Both scenarios limit the application of such kinds of free-space ONNs. Silicon-based integrated ONNs designed on a silicon-on-insulator (SOI) platform are fabricated through CMOS-compatible processes, enabling cost-effective mass production via advanced photolithography and exposure techniques. This approach can simultaneously address the issues encountered by non-integrated spatial bulk ONNs. This section will introduce silicon-based integrated interferometric ONNs [39–47], integrated wavelength-division ONNs [48–59], integrated diffractive ONNs [60–63], and other silicon-based integrated ONNs [64–69].

1.3.1 *Silicon-Based Integrated Interferometric ONNs*

In 2017, Shen et al. [39] proposed an on-chip interferometric ONN based on a SOI platform. The team utilized 56 programmable MZIs to complete the optical matrix multiplication in a topological cascading manner, thus realizing the matrix operations of the neural network. The specific operation was to decompose any real-valued matrix \mathbf{M} into a diagonal matrix $\mathbf{\Sigma}$ and two unitary matrices \mathbf{U} and \mathbf{V} through the singular value decomposition method, i.e., $\mathbf{M} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^\dagger$, where the symbol ‘ \dagger ’ denoted the conjugate operation of matrix \mathbf{V} . Theoretical analysis showed that \mathbf{U} and \mathbf{V}^\dagger in any unitary matrix transformation could be realized by optical beam splitters and phase shifters. The diagonal matrix $\mathbf{\Sigma}$ could be realized by optical attenuators. These functions could be realized in physical devices through the topological cascading of MZIs. In 2018, Hughes et al. [40] proposed an in-situ training method based on cascading MZIs to optimize the structure parameters of ONNs, making the training of ONNs more efficient. In 2021, Zhang et al. [44] designed a complex-valued ONN based on the MZI mesh. This work simultaneously utilized the phase and amplitude of light, thereby increasing the number of adjustable variables in the network.

This design method improved the performance of ONNs based on MZIs, significantly enhancing the ONN's computing speed and energy efficiency. Additionally, the learning capabilities of the complex-valued neural network, including classification accuracy and the convergence speed of the loss function, were superior to those of real-valued neural networks. In this study, the complex-valued neural network was used to complete tasks such as logic gate operations, IRIS dataset category prediction, nonlinear data (circle and spiral) classification, and MNIST dataset category prediction. The following year, Zhu et al. [46] introduced diffraction units (implementing the function of the Fourier transform and the inverse Fourier transform) into the MZI mesh. Regarding the same MNIST and Fashion-MNIST dataset classification experiments, combining MZI mesh and diffraction units reduced the area and energy consumption of the entire ONNs to 1/10 of that of ONNs implemented with only traditional MZIs.

1.3.2 Silicon-Based Integrated WDM-System ONNs

In 2019, Feldmann et al. [51] adopted micro-ring wavelength division multiplexing (WDM) systems and PCM materials based on the Si_3N_4 platform to design on-chip optical devices that imitate the functions of neurons and synapses. When these devices were constructed into a network or neuromorphic system, they processed information in a way that was more like the human brain. During the implementation of these ONNs, the input pulses were weighted through PCM units. Then, the corresponding wavelength of light was coupled into a single-mode waveguide through the micro-ring for power addition. When the integrated power in the single-mode waveguide exceeded a certain threshold, the PCM unit on the last ring resonator switched and generated an output pulse, thus completing a reasoning calculation on the optical domain. During this calculation, the nonlinear function was directly realized optically. In 2021, Feldmann et al. [55] implemented an integrated photonic tensor core on the Si_3N_4 platform based on micro-ring WDM systems and PCM, which realized the parallel processing function of traditional convolutional kernels on the chip. It could run at a speed of trillions of operations per second (i.e., 10^{12} multiply-accumulate operations per second). This work utilized PCM material storage arrays and optical frequency combs based on the photonic chip to realize parallel photonic memory computing, which could operate at a bandwidth of over 14 GHz, and its computing speed was limited only by the modulator and photoelectric detector speed. In the same year, Huang et al. [56] designed a WDM-system ONN based on an SOI platform, which was used to compensate for the nonlinear problems in submarine optical fiber transmission systems. The reconfigurable WDM-system ONN could process optical signals in the analog domain, significantly alleviating the stringent requirements of traditional digital signal processing circuits in terms of complexity and speed. In 2023, Bai et al. [59] designed a photonic processing unit using an on-chip micro-ring WDM system, which included multiple wavelength sources, data loading areas, and data processing centers. The photonic processing unit could use

the time-wavelength plane stretching method to implement the convolution function, with a computing density of approximately 1.04 TOPS per square millimeter (i.e., approximately 1 trillion operations per square millimeter per second), which was five times the highest computing density of any silicon-based integrated WDM-system ONNs before. The convolutional neural network designed based on the photonic processing unit achieved image edge detection quality and MNIST data recognition accuracy (96.6%) which was comparable to the detection and recognition results of its electrical counterparts.

1.3.3 Silicon-Based Integrated Diffractive ONNs

Silicon-based integrated ONNs implemented based on the cascading MZI mesh or micro-ring WDM system have overcome issues such as the large volume, poor portability and stability of free-space DONNs, and possible system errors caused by the alignment and calibration process of discrete optical components. However, both silicon-based integrated ONNs realized by MZI topology cascading and those realized by micro-ring WDM systems have a common problem: low computing capacity. To solve this problem, research on silicon-based integrated DONNs has been reported one after another [60–62]. In 2020, Zarei et al. [60] designed a silicon-based integrated DONN with subwavelength rectangular micro-slot structures and verified its performance in a simulation manner. The silicon-based integrated DONN had a very high integration degree, with a theoretical calculation of approximately 3.75×10^4 neurons per square millimeter, and its computing capacity was about 1.54×10^{16} operations per square millimeter per second, i.e., 1.54×10^4 TOPS. In 2022, Zarei et al. [62] used the silicon-based integrated DONN to realize the logical gate operation function. In the same year, Wang et al. [61] experimentally realized the silicon-based integrated DONN designed with subwavelength rectangular micro-slot arrays (metalines). The area of the silicon-based integrated DONN was about 0.135 mm^2 , and the theoretical calculation showed that approximately 6.7×10^3 neurons could be integrated per square millimeter. Before the research on silicon-based integrated DONNs began, some studies had already been related to silicon-based on-chip diffraction, such as on-chip lenses [70, 71].

1.3.4 Other Integrated ONNs

Other integrated ONNs [64–68] refer to neural networks constructed with two-dimensional silicon-based integrated optical waveguides, on-chip multi-mode interferometers (MMIs), phase shifters or attenuators, and three-dimensional integrated optical waveguides and other optical components. In 2020, Moughames et al. [65]

used two-photon polymer printing technology to fabricate a three-dimensional integrated low-loss photonic waveguide array, where the diameter of the photonic waveguide was $1.2\ \mu\text{m}$, the spacing between adjacent waveguides was $20\ \mu\text{m}$, and approximately 2200 neurons could be integrated per cubic millimeter. In the same year, Qu et al. [66] used reverse engineering to design and fabricate silicon-based nanophotonic scattering units. The optical scattering units were fabricated within $4 \times 4\ \mu\text{m}$ through reverse design. This was achieved by fabricating nanopatterns with high degrees of freedom in the MMI region. Theoretically, these optical scattering units could also perform arbitrary unitary matrix multiplication. Based on this result, the team designed a silicon-based integrated ONN for the MNIST dataset and achieved a blind test accuracy of 97.1% on the MNIST testing set. In 2022, Ashtiani et al. [68] adopted carrier doping technology to fabricate electrically controlled tunable attenuators on silicon waveguides. Thus, the weight configuration of the neural network could be realized by adjusting the attenuation coefficient of each waveguide. The optical power output from each waveguide would be collected separately by multiple PDs and then it would be output through a micro-ring modulator designed based on carrier injection. This process could be used to realize optical nonlinear functions. The silicon-based integrated system could only perform a single neuron operation simultaneously. To complete a matrix operation, it was necessary to adjust the attenuator coefficients multiple times.

1.4 Research Significance and Objectives

In summary, the lithography precision of semiconductor manufacturing processes has approached the physical limit of transistors. Meanwhile, with the rapid development of artificial intelligence, neural network algorithms will require more computing resources and energy consumption. However, the current electronic computing hardware will be unable to meet future computing demands. ONNs are a potential solution to this problem, but current free-space DONNs are composed of discrete optical components, so they are large, have poor stability, and have poor portability. The fabrication of integrated ONNs based on the CMOS substrate is highly challenging, the cost of mass production is prohibitively expensive, and the reconfigurability of computing units on the interlayer diffraction plates is also extremely difficult to achieve. For silicon-based integrated ONNs other than integrated DONNs, the computing units need continuous energy supply during operation. Additionally, the relatively large size of these computing units poses a challenge to large-scale expansion, resulting in the generally low computing capacity of this type of silicon-based integrated ONNs. However, in the past three years, for silicon-based integrated DONNs, apart from the experimental work by Wang et al. [61] in 2022, other studies have been confined to the theoretical calculation stage [60, 62, 72]. In addition, in the work proposed by Wang et al. [61], signal loading is achieved through the combination of lens groups and DMD, which has not been realized in a silicon-integrated manner. Furthermore, there has been no in-depth exploration of the weight mapping

Table 1.1 Research objectives of this thesis

Parameters	Dimension	Size of the computing unit	Theoretical integration degree (computing units/ mm ²)	Energy efficiency	Stability/ portability	Computing speed (operations/ s)
Objective	Integrated	$\leq 1.5\mu\text{m} \times 2\mu\text{m}$	$\sim 10^3$	High	Good	$>10^{12}$

model for the on-chip structure parameters of silicon-based integrated DONN. Also, there has been no mention of the compensation scheme and related measures for the experimental system error during the experiment. At present, there is no comprehensive research on silicon-based integrated DONNs, such as the forward propagation model of silicon-based integrated DONNs, the weight mapping rules for the structure parameters of integrated DONNs, and the practical problems that may be encountered in experimental fabrication, packaging, and testing of the integrated DONN chips.

Therefore, this thesis will conduct a systematic study on aspects such as theoretical exploration, structure design, and simulation calculation of silicon-based integrated DONNs, as well as the fabrication, packaging, and testing aspects of silicon-based integrated DONN chips and compensation for experimental system errors. First, a silicon-based integrated DONN model will be built during the research process, including an on-chip forward propagation model, a silicon-based integrated DONN training model, and a weight mapping model. Second, corresponding silicon-based integrated DONN chips will be designed for various tasks, and their performance will be successfully verified through simulation and experiment. Additionally, since system errors are unavoidable in chip fabrication and experimental testing processes, this work will analyze system errors in detail and propose effective and feasible error compensation schemes. Finally, to further improve the performance of silicon-based integrated DONN chips, a design method for the multi-functional silicon-based integrated DONN system architecture will be proposed. The research objectives are summarized in Table 1.1, and the research results will provide valuable references for the design and experimental work of silicon-based integrated DONN chips.

1.5 Main Content and Structure of the Thesis

This research aims to systematically study key scientific and technological issues related to silicon-based integrated DONNs, including the forward propagation model of the silicon-based integrated DONNs, namely the two-dimensional spatial domain electromagnetic propagation model (SDEPM), used to represent the propagation laws of light in silicon-based slab waveguides. The second is the phase weight mapping model of the silicon-based integrated DONNs, which ensures that the phase weight