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Review

Dendritic Learning for AI: A Survey of Models, Algorithms, Applications, and Future Directions

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Abstract: Dendritic learning is inspired by the brain's complex dendritic structures and biologically plausible learning mechanisms, and it exhibits substantial potential as a next-generation framework for biologically plausible artificial intelligence. Over the years, sustained research efforts have positioned dendritic learning as a promising and rapidly advancing direction in AI research. This paper presents a comprehensive survey of dendritic learning, encompassing its architectures, learning algorithms, and application domains. The main contents of this survey include: the neuroscience fundamentals of dendrites, a systematic review of existing dendritic learning architectures from the perspectives of dendritic plasticity and morphology, biologically plausible dendritic learning rules, a summary of real-world applications of dendritic learning, and an exploration of open questions and potential research directions in this field.

Keywords: dendritic learning; artificial intelligence; deep learning; biological plausibility

1. Introduction

Artificial intelligence (AI) has achieved tremendous success across a wide range of fields, including pattern recognition [1–3] and natural language processing [4]. In particular, deep learning [5] and large language models [6] have demonstrated remarkable performance, in some cases surpassing human capabilities. However, these advances come at the cost of massive computational demands and a heavy reliance on precisely labeled data, which remain major challenges. At a fundamental level, the McCulloch–Pitts (MCP) neuron is an oversimplified abstraction, as it relies solely on weighted summation operations [7]. Meanwhile, learning rules based on backpropagation (BP) diverge significantly from biological learning mechanisms and suffer from the weight transport problem. This requirement for symmetric forward and backward weights does not exist in the brain. Instead, synaptic weight adjustments follow Hebbian principles, whereby changes in synaptic strength are local and depend solely on the activities of pre- and postsynaptic neurons [8]. Reliance on such symmetric weight transport in artificial models limits local learning, biological plausibility [9], and interpretability [10]. Consequently, AI performance is strongly influenced by the interplay among network architectures, learning rules, and loss functions, which together determine how intelligent systems acquire and generalize knowledge [11]. To address these challenges, increasing attention has been directed toward AI models and learning rules that incorporate biological mechanisms, with the goal of improving both biological plausibility and expressive power. Dendritic learning represents a promising direction in this endeavor and has begun to guide innovative developments in AI architecture design and learning paradigms.

This survey focuses on biologically inspired dendritic learning, motivated by the intrinsic advantages and strong scalability exhibited by dendrites in the biological brain. Dendrites play a critical role in higher-order cognitive functions such as learning [12–14], memory [15–17], and perception [18–20]. Compared with traditional MCP-based models, dendritic learning refines the functionality of basic computational units, offering greater expressive capacity and architectural flexibility as well as biological plausibility. In recent years, extensive interdisciplinary research has actively explored dendritic learning, leading to the development of diverse dendritic learning and yielding significant progress across multiple application domains [21–23]. This rapid growth underscores the need for a systematic review to help researchers understand the overall landscape of dendritic learning and to

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comprehensively grasp its current achievements and open challenges.

To enhance the readability and retrievability of the survey across different disciplines, the survey adopts a four-layer structured taxonomy, organized based on the neuroscientific fundamentals of dendrites, dendritic learning architecture, dendritic learning rules, and applications. This classification method offers several advantages: (1) it allows researchers to first identify the biological principles underlying dendritic computation; (2) it clarifies how novel architectures inspired by these principles address limitations of existing models; (3) it facilitates understanding of diverse dendritic learning rule paradigms; and (4) it highlights practical applications, thereby clarifying the real-world utility of dendritic learning. The main features and contributions of this paper are as follows:

(1) This survey analyzes the intrinsic characteristics and significance of dendritic learning from a neuroscientific perspective, revealing its fundamental structural and functional features.
(2) This survey systematically reviews dendritic learning models and learning rules, summarizing their strengths and limitations, and categorizing their developmental trajectories and application scenarios to provide a comprehensive reference for neural network researchers.
(3) This survey discusses current challenges and outline future research directions for dendritic learning.

The remainder of this paper is organized as follows. Section 2 introduces the neuroscientific foundations of dendrites relevant to artificial intelligence. Section 3 presents an overview of dendritic learning–based model architectures; within this section, dendritic architectures and learning rules are reviewed in Sections 3.2 and 3.3, respectively. Section 3.4 surveys applications of dendritic learning. Section 4 discusses open challenges and future research directions, and finally, Section 5 concludes the paper.

2. Neuroscience Fundamentals of Dendrites

Dendrites are fundamental to brain function [24]. They receive and integrate sensory information and play critical roles in learning, recognition, memory, and other cognitive processes. Dendrites exhibit advanced characteristics that differ substantially from those of traditional artificial neural networks, including nonlinear dendritic integration and flexible, adaptive dendritic morphology. These properties provide essential neuroscientific foundations for dendritic learning from multiple complementary perspectives. Figure 1 illustrates the neuroscience fundamentals and inspirations of dendrites.

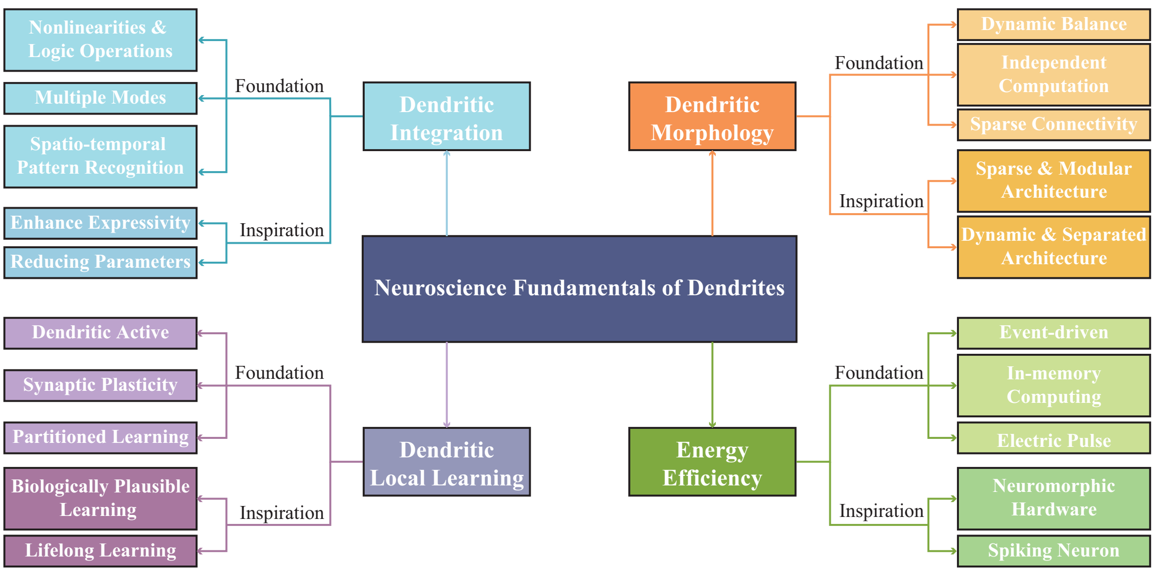

Figure 1. The research paradigm on dendritic learning according to the neuroscience fundamentals of dendrites.

2.1. Dendritic Integration

The traditional artificial neuron is a linear computational unit that applies weighted summation to its inputs. In contrast, biological evidence shows that dendrites are active processing elements rather than passive cables [25]. As early as 1987, studies demonstrated that dendrites possess active ion channels (e.g., NMDA, Ca^{2+}, and Na^{+}), enabling them to generate nonlinear responses [26]. These dendritic integration allow dendrites to perform nonlinear computations and even implement logical operations (e.g., AND, OR, XOR) within a single neuron. In particular, dendritic calcium action potentials (dCaAPs) in human L2/3 pyramidal neurons enable single neurons to solve linearly inseparable XOR problems, which traditionally require multilayer networks [24]. Moreover, dendritic integration can operate in multiple modes depending on the location and strength of synaptic inputs, including linear integration [27], sublinear integration [28–30], and supralinear integration [31–33]. These findings indicate that dendrites have the ability to receive and integrate sensory information through diverse functional mechanisms, significantly enhancing the expressive power of single neurons and thereby reducing the required number of parameters in neural models [34].

Furthermore, dendritic integration enables neurons to exhibit sensitivity to the spatial arrangement and temporal synchrony of inputs [35,36], enhancing neuronal responses to specific sensory features. As a result, dendrites support various forms of feature selectivity, such as direction selectivity [37] and orientation selectivity [38]. This intrinsic property allows neurons to extract complex spatiotemporal features rather than merely processing static vectors or tensors. In contrast, traditional artificial neurons only approximate a limited subset of dendritic functions. Therefore, dendritic integration provides a strong biological foundation for guiding the design of more expressive fundamental neural units in artificial intelligence, addressing the limitations of MCP neurons and improving representational capacity.

2.2. Dendritic Morphology

Another core aspect of dendritic learning is its close relationship with dendritic morphology. Dendritic morphology not only provides the physical basis for receiving synaptic inputs but also enables functional compartmentalization of neuronal computation [39]. Variations in dendritic morphology lead to differences in electrical impedance, allowing distinct dendritic branches to operate as semi-independent computational units [40]. For example, the apical and basal dendrites of layer-5 pyramidal neurons can be electrically segregated, preferentially processing top-down and bottom-up signals, respectively [41]. Moreover, dendritic morphology directly influences the size of receptive fields as well as the type and density of synaptic inputs [42], giving rise to diverse dendritic structures with multifunctional properties. Notably, the asymmetric and multi-branch morphology of dendrites is also not randomly formed [43], it emerges as a sophisticated computational architecture shaped by environmental signals, cytoskeletal dynamics, and self-avoidance mechanisms [44]. Dendrites must actively balance morphological complexity and receptive field coverage through regulated branching processes [45,46]. These studies suggest that neuronal structure is inherently dynamic and asymmetric. However, such biological principles have not yet been fully incorporated into the design of current artificial intelligence models.

Meanwhile, dendritic morphology also determines the modes of dendritic integration [47]. Consequently, the joint effect of dendritic morphology and integration enables a single neuron to function analogously to a deep neural network [48]. Complex dendritic integration endows a single cortical pyramidal neuron with input–output mapping capabilities comparable to those of a 5- to 8-layer deep neural network, further demonstrating the expressive superiority conferred by dendritic morphology [49].

In addition, biological neural connectivity is highly sparse and structured, with synapses serving specific functions often clustering on particular dendritic branches [50,51]. This observation suggests that artificial intelligence models should move beyond fully connected layers toward sparse and modular architectures inspired by dendritic morphology. By introducing dendritic branches as computational units, the input space can be partitioned across specialized processing modules, thereby reducing computational complexity while enhancing generalization capability.

2.3. Dendritic Local Learning

Learning paradigms significantly impact the performance of artificial intelligence models. However, in biological brains, error signals are not computed globally through backpropagation [52]. Instead, apical dendrites receive prediction errors or feedback signals from higher cortical areas, which locally guide synaptic plasticity [53,54]. This mechanism enables neurons to exploit local information for coordinated learning across multilayer networks. Dendritic learning thus provides biologically plausible alternatives for addressing this fundamental challenge.

The generation of local error signals involves calcium plateau potentials and neuronal bursting. When apical dendrites receive sufficiently strong feedback signals, they generate calcium spikes or plateau potentials. This local depolarization propagates to the soma, triggering high-frequency bursting action potentials [11]. Such bursting activity is widely regarded as a local teaching signal that guides synaptic plasticity, indicating whether synapses on basal dendrites should be strengthened [55]. Concurrently, theoretical models suggest that inhibitory inputs can locally balance excitatory inputs at the level of individual dendritic branches [56]. When this local balance is disrupted, the resulting dendritic membrane potential encodes an error signal. Synaptic weight updates then depend solely on this local membrane potential and postsynaptic spiking activity, enabling error-based learning without global error propagation [25]. Dendritic branches allow synaptic inputs to induce substantial local voltage changes, and this passive amplification facilitates electrical interactions among co-activated inputs. Such interactions form the basis of dendritic nonlinear processing and local learning mechanisms [57].

Meanwhile, dendrites support multiple synaptic plasticity mechanisms within a single neuron [58]. They also enhance memory retention by enabling compartmentalized storage of information. Different tasks or memories can be allocated to distinct dendritic branches, thereby reducing interference. New learning tasks can be accommodated on newly formed branches through structural plasticity, including synapse formation and elimination, while preserving previously acquired knowledge [59, 60]. These biologically plausible learning mechanisms offer promising pathways for overcoming the inherent limitations of backpropagation-based learning.

2.4. Energy Efficiency

Currently, the training of AI models requires extensive computational resources. By contrast, the biological brain operates with extremely low power consumption (approximately 20 W), which stands in stark contrast to the high energy demands of contemporary AI systems. Dendritic learning provides a blueprint for achieving low-power artificial intelligence. In the brain, dendrite is spike-based, consuming energy only when specific events occur. This spatiotemporal sparsity significantly reduces power consumption [61].

Moreover, computation (membrane potential integration) and storage (synaptic weights) are physically co-located within dendrites, eliminating the substantial energy expenditure associated with frequent data movement [62]. In addition, excitatory and inhibitory inputs on dendrites maintain a local dynamic equilibrium. This mechanism has been shown to guide efficient representational learning while reducing redundant neuronal firing [63].

2.5. Inspiration for AI

Dendritic integration can substantially enhance the expressive capacity of single neurons. Incorporating dendritic nonlinearities into foundational AI models significantly increases their representational power, enabling them to solve complex problems with fewer parameters. Simultaneously, leveraging dendritic delay and integration properties allows the construction of networks capable of processing temporal information without relying on recurrent connections. Furthermore, dendritic morphology inspires AI models to transition from fully connected architectures toward sparse and modular designs. By introducing dendritic branches as computational units, the input space can be partitioned across distinct processing modules, thereby reducing computational complexity while improving generalization. AI models can further incorporate dendritic branch protection mechanisms. During the learning of new tasks, weights critical to previously learned tasks can be frozen, while unused branches or silent synapses are recruited for new knowledge acquisition, enabling lifelong learning. Learning rules based on local dendritic error signals can replace global backpropagation. This approach is not only more biologically plausible but also reduces memory and communication overhead during training, making it well suited for neuromorphic hardware implementations. Additionally, introducing spiking signals into neural networks lowers average firing rates and enables the learning of more efficient input representations, even in the presence of transmission delays.

In summary, integrating dendritic learning into the construction of foundational AI models fundamentally expands computational units from point-like abstractions to structured entities. This transformation exploits dendritic integration to achieve deep computational capabilities within single neurons, leverages dendritic morphology for functional modularity and parallelism, mitigates the biological implausibility and catastrophic forgetting associated with backpropagation through local learning rules, and ultimately realizes brain-inspired, high-efficiency computation via event-driven mechanisms. Together, these principles provide a clear pathway toward next-generation AI systems that are more powerful, energy-efficient, and capable of sustained lifelong learning.

3. Dendritic Learning

Based on the neuroscientific foundations of dendrites, dendritic learning has emerged as a promising approach for addressing key challenges in AI, paving the way toward next-generation learning systems that are more powerful, energy-efficient, and interpretable. Dendritic learning incorporates the advantages of dendrites, such as nonlinear integration, synaptic plasticity, and morphological diversity, into both network construction and learning mechanisms. In this section, an abstract definition of dendritic learning is presented to clarify its core principles, followed by a review of dendritic learning–based architectures and learning rules, as well as its applications.

3.1. Definition

In dendritic learning, dendrites exhibit distinct activation and integration mechanisms for incoming signals. Figure 2 illustrates a schematic comparison between artificial neural networks and dendritic learning. Dendritic learning possesses diverse types of neuronal units that exhibit differential activation to different input pairs based on synaptic plasticity, unlike the uniform activation characteristic of traditional models. Furthermore, its flexible sparse connectivity architecture effectively reduces the number of model parameters. Accordingly, an abstract formulation of dendritic learning can be described as follows:

$$y_d = f\left(\underbrace{I\left(\mathbf{W}_i\,\overbrace{\sigma(x_i)}^{\text{Plasticity}}\right)}_{\text{Integration}} + \underbrace{\sum_m h_m y_m}_{\text{Morphology}} + b_d\right) \tag{1}$$

where $\sigma(\cdot)$ denotes synaptic plasticity, which modulates the receptive field, type, and density of synaptic signals. $\mathbf{W}_i$ represents synaptic weights, and $I(\cdot)$ denotes the dendritic integration operator, which can implement different forms of integration depending on synaptic activity patterns. b_d is the dendritic bias term.

Notably, due to the diversity of dendritic morphology, each dendritic branch may influence other branches (including itself) through coupling strengths h_m, capturing inter-branch interactions arising from morphological and electrical connectivity. Furthermore, dendritic local learning can be expressed as:

$$\Delta \mathbf{W} = \eta \underbrace{\phi(V_a)}_{\text{Post-synaptic}} \underbrace{(V_a - V_b)}_{\text{Local Error}} \underbrace{\mathbf{x}_i}_{\text{Pre-synaptic}} \tag{2}$$

where V_a and V_b denote the apical and basal voltage, η is the learning rate.

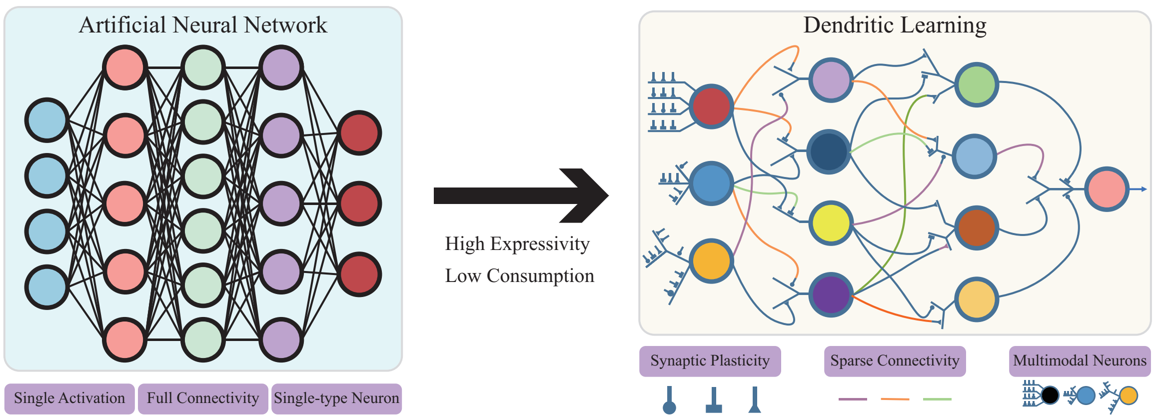

Figure 2. The illustration of dendritic learning.

3.2. Architectures

Inspired by the biological advantages of dendrites, a variety of dendritic learning models have emerged to address the limitations of current artificial intelligence systems. Some studies incorporate dendritic nonlinearities into fundamental computational units to overcome the expressivity constraints of MCP neurons. Others integrate biophysical principles into model design by leveraging dendritic morphology, extending these concepts to neuromorphic architecture modeling. In addition, certain works explicitly simulate dendritic spike dynamics for neuromorphic computation. Owing to the inherent interpretability of dendritic structures, several mathematically grounded high-order architectures have also been proposed. Overall, existing dendritic learning approaches can be broadly categorized into four classes: single dendritic neuron models, biophysical architectures, dendritic spiking architectures, and biologically interpretable architectures. Table 1 compares representative dendritic learning architectures.

3.2.1. Single Dendritic Neuron Model

To address the limited expressivity of MCP neurons, numerous studies have exploited the high representational capacity of dendrites to construct biologically realistic neurons with complex dendritic structures. Researchers have progressively explored the essence of dendritic learning, evolving from early simulations of nonlinear computation in single neurons to increasingly sophisticated network architectures and deep learning–integrated models. An early dendritic neuron model (DNM) [64] is proposed to enhance the expressive power of a single neuron by incorporating synaptic, dendritic, membrane, and somatic layers. In this model, the synaptic layer employs sigmoid activation functions with learnable parameters to process inputs, enabling four types of synaptic connections (excitatory, inhibitory, constant-0, and constant-1 connections) [65], i.e.,

$$Y_{i,j} = \frac{1}{1 + e^{-k(w_{i,j}x_i - \theta_{i,j})}} \tag{3}$$

where $w_{i,j}$ and $\theta_{i,j}$ denote the weight and bias of the ith input on the jth dendritic branch, respectively, and k represents synaptic strength.

Table 1. Summary of representative dendritic learning architectures, BA: Bio-inspired Algorithms, SP: Structural Plasticity, LE: Local Error, DN: Dendritic Normalisation, PSP: Post synaptic potentials, TP: Target Propagation.

Model	Scalability	Complexity	Learning Rules	Features
DNMs [64,65]	Large	Large	BP & BA	Incorporates a comprehensive dendritic structure with synaptic, dendritic, membrane, and somatic layers, exhibiting stronger computational capacity than MCP neurons.
Logic DNM [66,67]	Large	Large	BP	Utilizes pruning functions to eliminate redundant branches; trained DNMs can be converted into logic circuits (such as comparators and logic gates).
C-/Q-DNM [68]	Large	Large	BP	Extends DNM to complex-valued and quaternion domains, enabling the processing of high-dimensional and complex data.
Clusteron [69,70]	Medium	Medium	SP& BP	Simulates the spatial clustering of synapses on dendrites. GClusteron combines structural plasticity with gradient descent to solve the XOR problem.
MDPN [71]	Medium	Low	BP	Abandons linear summation mechanisms, adopting nonlinear dendritic computation to enhance neural plasticity. Constructs a lightweight and efficient classification system via single neurons.
ccRNN [72]	Large	Large	BP & LE	Establishes a natural link between deep learning and neuroscience, and provides theoretical support for classic cerebellar models.
PyNADA [73]	Medium	Medium	BP	Mimics cortical pyramidal neurons by separating input pathways for basal dendrites (ReLU) and apical dendrites (ADA activation function).
NLD [74]	Medium	Low	SP	Adopts sparse connectivity matrices and utilizes nonlinear dendritic processing mechanisms to achieve high classification accuracy.
Sparse [75]	Larger	Larger	DN	Uses sparse connectivity and binary weights, or mimics independent computational units of dendritic branches, reducing computational overhead and improving robustness.
Dendritic FF [76]	Larger	Larger	PSP	Introduces simplified dendritic filtering mechanisms into the standard Integrate-and-Fire (IF) model, enhancing spatiotemporal pattern recognition capabilities.
DPAP [77]	Larger	Larger	BP	Performs adaptive network pruning based on dendritic spine formation and elimination mechanisms (dependent on LTP/LTD).
Dendritic spik [78]	Larger	Larger	TP	Systems with binary synapses can be trained using structural plasticity algorithms, achieving classification accuracy comparable to traditional algorithms while consuming fewer synaptic resources.
DD [79]	Low	Low	BP	A white-box model where core operations are matrix multiplication and Hadamard products. It can be expanded into polynomial forms, possessing interpretability similar to Taylor series.
PDN [80]	Low	Low	BP	Outputs explicit high-order polynomial representations of inputs; a single neuron can realize XOR logic.
PiDKAN [81]	Low	Low	BP	Integrates Pi-Sigma networks, DNM, and KAN (Kolmogorov-Arnold Network), featuring full differentiability and explicit physical interpretation.

The dendritic layer then integrates synaptic signals using a multiplicative operation, $Z_j = \sum_{i=1}^{N} Y_{i,j}$, where N is the input dimension. Subsequently, the membrane layer aggregates signals from all dendritic branches through summation, $V = \sum_{j=1}^{M} Z_j$, where M denotes the number of dendrites. Finally, the soma layer produces the neuron output as $O = \sigma(V - \theta_s)$. This hierarchical structure not only provides deeper insight into biological neuronal computation but also offers a practical and powerful framework for solving real-world problems. Notably, studies have shown that a single DNM can outperform conventional multilayer networks in certain tasks [82].

Despite these advantages, the initial DNM suffers from several limitations, including sensitivity to initialization and hyperparameters, gradient vanishing, and training instability. To address initialization sensitivity, Luo et al. [83] proposed a decision-tree-based parameter initialization strategy, which reduces the required number of dendritic branches and enables faster convergence with improved classification accuracy. Building on this work, they further introduced the concept of learner interpretability diversity to quantify the differences between interpretable base learners prior to training, leveraging the biological plausibility of DNMs [84]. This diversity measure allows DNMs to achieve superior performance in both accuracy and energy efficiency. Moreover, to mitigate hyperparameter sensitivity across different applications, the adaptive strategy can dynamically adjust hyperparameters using differential evolution algorithms. To address the gradient vanishing problem, a residual connection between synaptic and dendritic layers is introduced to construct multilayer DNM architectures [85], significantly improving training stability and enabling application to more complex prediction tasks.

Furthermore, Todo et al. [86] proposed a delta-rule-based unsupervised learning method for training DNMs in simple scenarios, demonstrating their superior computational capability compared to MCP neurons. However, due to training limitations and gradient issues, DNMs remain challenging to scale to large and complex problems. To overcome gradient issue, an alternating excitation–inhibition mechanism is introduced to alleviate gradient vanishing caused by multiplicative operations in deep DNM stacks [87]. By replacing pure multiplication with bitwise or additive operations, they facilitated the construction of deeper dendritic networks. In parallel, Gao et al. [88] developed a series of metaheuristic optimization algorithms to enhance DNM training stability and broaden their applicability. Their results showed improved performance in classification, prediction, and function approximation tasks, with biogeography-based optimization achieving the best results. Consequently, numerous studies have explored alternative metaheuristic algorithms for training DNMs [89–97]. Beyond real-valued domains, DNMs have been extended to complex and higher-dimensional representations. They [68] extended DNMs to the complex-valued domain using fully complex-valued activation functions, providing rigorous mathematical analysis and extensive experimental validation of stability and learnability. Yu et al. [98] further explored DNMs in higher-dimensional spaces by proposing quaternion-based DNMs and deriving corresponding backpropagation rules, significantly expanding the scope of DNM applications.

Additionally, dendritic morphology in DNMs can be implicitly determined through the four synaptic connection types and multiplicative operations. The DNM structure is highly flexible, and trained DNMs can be pruned using pruning functions [66]. Dendritic branches with constant-0 connections can be eliminated, since multiplication by zero nullifies all inputs, while synapses with constant-1 connections can also be removed, as multiplication by one leaves inputs unchanged. As a result, pruned DNMs can be implemented as logical circuits [67]. However, pruning and training in conventional DNMs are asynchronous, as pruning is typically applied only after training on a static architecture. To address this limitation, dynamic structural adaptation methods have been proposed to improve computational efficiency and yield more compact architectures. Ji et al. [99] proposed a decomposition-based multi-objective architecture search framework that dynamically adjusts DNM structures during training. Furthermore, Wang et al. [100] introduced evolutionary DNMs, in which hyperparameters are encoded into the decision space of metaheuristic algorithms for joint optimization. These logical and structural properties enable DNMs to achieve highly energy-efficient and lightweight deployment.

Since DNMs are inherently single-output neurons, they face challenges in handling multi-output regression and classification tasks. To address this issue, Peng et al. [101] constructed dendritic networks composed of multiple DNMs. Similarly, Wang et al. [102] replaced MCP neurons with DNMs in fully connected layers and combined them with convolutional neural networks to enhance image recognition performance. Ding et al. [103] introduced a learnable filtering matrix and a telodendron layer into the somatic layer, breaking the single-output limitation and enabling adaptive dendrite selection for multi-regression tasks. Tang et al. [104] further proposed a trainable multi-output dendritic neural network capable of efficiently handling high-dimensional and multiclass tasks while preserving dendritic-inspired nonlinear computation.

In summary, DNMs exhibit superior computational capability compared to MCP neurons. Their architecture more closely resembles biological neurons by explicitly modeling synapses, dendrites, membranes, and somata, each with clear physical interpretation. DNMs also support structural pruning, eliminating redundant synapses and dendritic branches to simplify network architecture. The resulting streamlined DNMs can be converted into logic circuits composed of comparators and logic gates, making them well suited for hardware implementation with fast computation and low power consumption. Nevertheless, challenges remain, including scalability to high-dimensional problems, sensitivity to initialization, and training difficulty, which motivate continued research into more robust and scalable dendritic learning frameworks.

3.2.2. Biophysical Architectures

Accumulating research evidence has decisively shown that dendrites leverage biophysical mechanisms to participate in sophisticated computations [105], thereby motivating the development of biophysically inspired architectures. These architectures aim to mimic the detailed structural and functional characteristics of dendritic neurons and their networks. By incorporating complex dendritic morphology, membrane potential dynamics, and specific synaptic plasticity mechanisms, biophysical architectures enhance computational power, storage capacity, and learning efficiency.

Building on the nonlinear properties of NMDA receptors [106], whose channels are voltage-dependent, Mel et al. [69] proposed the Clusteron model that represents a dendrite with multiple synaptic locations, where learning does not modify synaptic weights but instead relies on structural plasticity. In this model, multiple synapses are simultaneously activated within the same local dendritic region (i.e., a cluster), generating a superlinear voltage response rather than a simple linear summation. Specifically, underperforming synapses are randomly relocated to new dendritic positions, spatially reorganizing inputs to cluster correlated features. Building upon this idea, Moldwin et al. [70] proposed the GClusteron, which introduces continuous-valued synaptic positions and a distance-based smooth nonlinear function. The formulation enables the derivation of position update rules via gradient descent. Unlike the random relocation strategy of the Clusteron, GClusteron optimizes synaptic positions by allowing synapses associated with related inputs to attract or repel each other. The work demonstrates that updating either synaptic positions or weights alone is insufficient. However, by jointly combining structural plasticity and functional plasticity, the GClusteron can solve linearly inseparable XOR problems from arbitrary initial conditions. It effectively bridges biological structural plasticity with gradient-based optimization in modern machine learning

Poirazi and Mel [107] demonstrated that complex pyramidal neurons are not merely point processors, their dendritic trees contain numerous independent nonlinear integrative subunits. Bredenberg et al. [108] further showed that reproducing the input–output transformations of layer-5 pyramidal neurons (L5PCs) with millisecond-level accuracy requires a deep temporal convolutional neural network with 5 to 8 layers, based on detailed biophysical models of L5 and layer-2/3 pyramidal cells. This finding highlights the depth and complexity of computations occurring within single pyramidal neurons. Therefore, Zhang et al. [71] constructed a lightweight dendritic pyramidal neuron model to enhance plasticity and improve image recognition accuracy through nonlinear neural plasticity mechanisms. Inspired by the damped response dynamics observed in human cortical pyramidal neurons, Pemberton et al. [72] proposed a cortico–cerebellar recurrent neural network (ccRNN), which provides a natural link between deep learning and neuroscience, bridging modern neural networks with classical cerebellar models. Meanwhile, Georgescu et al. [73] proposed the PyNADA model. This model incorporates two distinct input pathways corresponding to basal and apical dendrites, employing ReLU and a novel ADA activation function, respectively. The PyNADA architecture enables a single neuron to solve linearly inseparable problems by exploiting dendritic compartmentalization. Based on it, PyNADA is used to replace the standard models for the performance improvements.

Additionally, architectures based on sparse connectivity have been proposed to mitigate noise sensitivity and reduce computational overhead. Jeon et al. [109] investigated neuronal and synaptic characteristics and their implications for sparse connectivity in artificial intelligence. Hussain et al. [74] simulated sparse connectivity and binary synaptic weights characteristic of biological synapses. By selecting only k key synapses for dendritic connection, their model exploits dendritic nonlinearities to compensate for the accuracy loss caused by binary weights while significantly reducing memory requirements. Wu et al. [110] combined pyramidal neuron properties with sparse connectivity to construct an intragroup sparsity model. Jiang et al. [111] adopted an active disorganized architecture in which each neuron processes only a small fraction of the input via random subspace sampling, achieving strong robustness to noise. Moreover, Li et al. [112] introduced adaptive dendritic units and learnable sparse masks to emulate the sparsity of biological synaptic connections. Their model dynamically adjusts connectivity patterns based on context, evolving from an initially random sparse structure into stable, task-relevant configurations. Jones et al. [113] designed a sparse neural network with a binary tree structure, where each node receives only two inputs and applies nonlinear activation functions. By incorporating redundant inputs, this architecture can approximate the performance of fully connected networks while maintaining sparsity.

Furthermore, dendrites possess an inherent isolation property, with individual dendritic branches functioning as independent computational units that minimally interfere with one another. Guerguiev et al. [114] exploited the morphological segregation of basal and apical dendrites in cortical pyramidal neurons. In their model, basal dendrites integrate bottom-up sensory inputs, whereas apical dendrites process top-down feedback signals. This compartmentalization enables neurons to receive feedback for credit assignment without disrupting feedforward processing, thereby allowing local error computation without an explicit global error channel. Similarly, Sacramento et al. [115] proposed a simplified multi-compartment neuron model in which bottom-up inputs and top-down feedback converge on separate dendritic compartments. Prediction errors emerge at the apical dendrites when lateral interneuron activity fails to fully cancel top-down feedback, driving synaptic plasticity. Haider et al. [116] adopted a related architectural principle within a latent equilibrium framework. In addition, Peng et al. [117] leveraged active dendritic computation and feedback mechanisms to design a DeP system, in which dendrites serve as the primary information-processing units while the soma acts mainly as a storage component.

Although biophysically inspired models differ in their specific mechanisms and design philosophies, they collectively demonstrate effective strategies for alleviating key challenges in artificial intelligence model construction. These findings indicate that simulating dendritic biophysical mechanisms can yield computational models that are stable and lightweight. However, such approaches also exhibit notable limitations. In order to emulate biological characteristics, these models often sacrifice precise gradient computation or introduce complex temporal dynamics that complicate training and implementation. For example, while isolated dendrite–based models are capable of achieving deep learning behavior, increasing the number of hidden layers beyond two does not further reduce error rates, suggesting that this class of algorithms may struggle to scale to very deep architectures. Furthermore, many sparse neural network designs suffer from poor data locality, which can lead to inefficient memory access patterns and suboptimal inference performance on modern hardware.

3.2.3. Dendritic Spiking Architectures

Currently, artificial neural networks (ANNs) are predominantly based on continuous real-valued signals, with neuron outputs regulated through activation functions. In contrast, the biological brain transmits information via discrete electrical pulses, where synapses accumulate membrane potential and trigger activation once a threshold is reached. Consequently, the theory and applications of spiking neural networks (SNNs) and neuromorphic computing have been extensively studied. Despite their advantages, SNN neurons also face several challenges. Some research efforts focus on mimicking the multi-branched dendritic structures of biological neurons, leveraging nonlinear dendritic dynamics to enhance computational efficiency, logical reasoning capabilities and biological plausibility. For example, most spiking neuron models lack complex dendritic structures or explicit leakage mechanisms [118]. Pfeiffer et al. [119] emphasized the importance of multi-compartmental neuron models and spatially intricate dendritic structures in biological information processing, indicating that dendritic mechanisms enable nonlinear computation and local learning rules that are critical for resolving the credit assignment problem. Similarly, Li et al. [120] highlighted dendritic processing as a key factor in improving biological plausibility and exploiting the full potential of SNNs.

To alleviate the above limitations, dendritic spiking architectures are proposed. Hussain et al. [121] proposed a neuron model with nonlinear dendrites and structural plasticity learning rules for binary pattern classification. However, the enhanced nonlinear function in their model is later interpreted as a form of dendritic leakage. Building on this insight, Bhaduri et al. [78] explicitly introduced a dendritic leakage mechanism by subtracting a constant leakage term from the total synaptic input current, thereby reducing the current entering the nonlinear module. They further proposed a spiking neural classifier with lumped dendritic nonlinearity. Meanwhile, Bird et al. [75] demonstrated that dendritic morphology itself can induce leakage effects. The larger dendritic trees, which receive more synaptic inputs, exhibit increased membrane leakage and signal attenuation. To address this, they proposed a dendritic normalization mechanism. By contrast, Beniaguev et al. [76] incorporated simplified dendrites into the standard integrate-and-fire (IF) model, introducing the filter-and-fire neuron model. In the framework, multiple postsynaptic potential filters process input spike sequences, and multiple synaptic contacts significantly enhance spatiotemporal pattern recognition and memory capacity. The model achieves nearly three times the capacity of standard IF neurons, highlighting the impact of dendritic structure on computational performance.

Chavlis et al. [122] further explored how biological dendritic features,including anatomical structure, active ion channel mechanisms, and multiscale plasticity, can be exploited to enhance computational performance, advocating dendritic branches with independent activation functions as fundamental computational nodes. Similarly, Grewal et al. [123] leveraged the morphological properties of L5 pyramidal neurons to construct a spatially isolated input model, in which bursting emerges through coincidence detection between basal and apical inputs, enabling target-based learning. Wang et al. [124] proposed the MMDEND model, a multi-branch, multi-cell parallel spiking dendritic neuron architecture. This model employs a state-space formulation to capture dendritic dynamics and enables parallel training. Its multi-branch structure handles long-range dependencies, while a scaling–shifting integer firing mechanism adapts to long-tailed membrane potential distributions, reducing quantization errors.

In addition, Zhang et al. [125] first introduced dendritic spine dynamic plasticity as a criterion for network pruning, where spine formation and elimination depend on postsynaptic firing patterns associated with long-term potentiation and depression. Spine density serves as an indicator of neuronal importance, guiding adaptive pruning of redundant synapses and neurons. Building upon this idea, Han et al. [77] proposed the DPAP pruning method, which integrates spine formation, growth, shrinkage, and elimination with BCM rules and neuronal firing traces to achieve adaptive structural pruning. Greedy et al. [126] introduced the BurstCCN multi-cell model for apical dendrite neurons, where burst ensemble multiplexing converts somatic spikes into high-frequency bursts. By incorporating dendritic interneurons and short-term plasticity, this model approximates single-phase backpropagation learning. Similarly, the GRAPES optimizer modulates a node's error signal based on its synaptic weight distribution, inspired by heterosynaptic competition and synaptic integration in cortical dendrites [127].

Overall, incorporating dendritic learning into SNNs significantly enhances their biological plausibility and computational capacity. Individual neurons become capable of solving linearly inseparable problems, such as XOR, substantially increasing per-neuron expressivity. Dendrites enable parallel signal processing across multiple branches, while dendritic spine–based grouping and pruning naturally induce network sparsity, reducing parameter counts and computational load. Dendritic compartmentalization and bursting mechanisms further support local and unsupervised learning, avoiding the need for globally propagated fine-grained error gradients as in traditional backpropagation. Nevertheless, dendritic SNNs also face notable challenges. Training remains difficult, and incorporating detailed dendritic morphology can dramatically increase computational cost, limiting scalability to large-scale networks. Achieving an effective balance between biological fidelity and computational efficiency remains an open problem. Moreover, dendritic SNNs currently lack a unified theoretical framework, and their performance is still constrained compared to mature deep learning paradigms.

3.2.4. Biologically Interpretable Architectures

Due to the intrinsic interpretability of dendritic structures, many researchers have developed biologically inteepretable architectures through mathematical modeling to mitigate the interpretability challenges of artificial intelligence models [128]. Kileel et al. [129] provided a mathematical foundation for polynomial networks by leveraging algebraic geometry. They interpreted the function space defined by a network as an algebraic variety and quantified the network's expressive power by computing its dimension, thereby making theoretical upper bounds transparent and computable. Building on this foundation, Liu et al. [79] introduced Dendrite Net (DD), a representative interpretable model inspired by dendritic properties. Its core operations consist solely of matrix multiplication and Hadamard products. Trained DD models can be expanded and simplified into explicit polynomial relationships between inputs and outputs, analogous to Taylor series expansions. The logical relationships learned by the model can be directly extracted through symbolic simplification. Experimental results show that it achieves higher test accuracy despite larger training losses, indicating strong generalization ability. To address redundancy arising from high-order computations, an acceleration module was subsequently proposed [130]. This module preserves DD's dendritic property, while significantly reducing computational complexity by minimizing multiplication and addition operations. Meanwhile, Chen et al. [80] proposed the polynomial dendritic neural network (PDN), which includes exponential and progressive variants. Trained using backpropagation, PDN outputs explicit high-order polynomial representations of the input. It inherits key advantages of dendritic learning, with even a single PDN neuron capable of implementing XOR logic, surpassing the representational limits of traditional artificial neurons.

Research has also shown that restricting information flow by mimicking the physical morphology of biological dendrites enhances transparency in decision pathways, thereby providing structural interpretability [113]. Building on this idea, Han et al. [131] developed a universal dendritic tree neuron module that emphasizes sparse, tree-like structures and local connectivity. By adjusting branching factors and input dropout, this architecture significantly improves performance while maintaining interpretability. Ojha et al. [132] proposed BNeuralT, which simulates the asymmetric structure of biological dendrites. It incorporates dendritic nonlinearities within internal nodes and establishes dedicated information-processing paths from leaves to the root. This explicit path structure yields a compact parameterization and offers greater logical interpretability than fully connected black-box networks. Chavlis et al. [21] introduced the dendritic artificial neural network (dANN), which employs two sparsely connected hidden layers and biologically inspired local receptive fields, while global receptive fields regulate input sampling. Unlike traditional ANNs that rely on category-specific units, dendritic nodes in dANN exhibit mixed selectivity, leading to enhanced robustness against noise and overfitting. The explicit connectivity structure allows the network's feature extraction mechanisms to be directly analyzed. Additionally, Saglam et al. [81] proposed the PiDKAN model, which integrates the Pi–Sigma network, dendritic neuron model, and Kolmogorov–Arnold Network (KAN). In this architecture, each synapse is modeled as a single-layer KAN unit that decomposes inputs into learnable univariate functions using splines. Higher-order feature interactions are captured through multiplicative aggregation via Pi–Sigma and dendritic operations. The entire model is fully differentiable, with both synaptic functions and dendritic branches possessing explicit mathematical formulations and physical interpretations. This design enables direct inspection of the nonlinear transformations learned at each synapse.

In summary, owing to their multiplicative and logical properties, biological dendrites are not merely linear summation units but are capable of performing multiplication and nonlinear transformations, thereby facilitating higher-order computation. Mathematically, these properties are typically modeled using Hadamard products, Pi–Sigma structures, or polynomial activations. Furthermore, dendritic architectures naturally constrain information flow, enabling biologically interpretable mappings between receptive fields and specific dendritic branches. However, such higher-order white-box architectures may suffer from redundant computations, while morphology-driven dendritic models often remain sensitive to distribution shifts, highlighting the need for balanced designs that reconcile interpretability, robustness, and efficiency.

3.3. Learning Rules

To address the biological unreliability of backpropagation (BP) learning, researchers have constructed numerous learning rules leveraging the biological characteristics of dendrites. These dendritic-based learning rules can be categorized into three main types: (1) dendritic morphology-based learning rules; (2) plasticity-based learning rules; and (3) bio-inspired algorithm-based learning rules.

3.3.1. Dendritic Morphology-Based Learning Rules

Pyramidal neurons exhibit a multi-compartment structure, in which apical dendrites receive feedback or contextual signals, while basal dendrites process feedforward inputs [133]. Building on this architecture, researchers have leveraged calcium plateau potentials as local error signals to address the weight transport problem and the reliance on global error propagation implied by backpropagation. Several studies utilize calcium plateau potentials generated in apical dendrites as guiding signals for learning [114,115]. These approaches estimate local errors by comparing activity differences across neuronal compartments and apical dendrites. Meanwhile, Golkar et al. [134] employed apical dendrites to receive feedback signals and simulate calcium potentials, updating synaptic weights using local, non-Hebbian learning rules. Similarly, apical and basal dendrites can be assigned to process distinct data streams, enabling unsupervised feature learning through decorrelation mechanisms mediated by lateral connections [135,136].

Furthermore, apical dendritic plasticity has been interpreted as a form of self-supervised learning, allowing neurons to learn complex probability distributions by predicting the likelihood of somatic spiking [137]. Exploring alternative learning mechanisms, Capone et al. [138,139] exploited the coincidence of basal and apical inputs to induce bursting activity, where learning is driven by matching internally generated burst patterns with target signals conveyed via apical dendrites. Lv et al. [140] proposed transmitting feedback signals to apical dendrites through independent trainable weights, enabling the computation of local errors from combined feedforward and feedback signals and the simultaneous update of forward and backward pathways.

Based on partial information decomposition, Makkeh et al. [141] enabled neurons to maximize redundant information between receptive field inputs and contextual inputs, resulting in highly interpretable local supervision signals. Leveraging dendritic isolation properties, Wang et al. [142] introduced a three-layer multi-compartment network in which apical dendrites address credit assignment. They further incorporated spike-frequency adaptation as a teaching signal to enhance the signal-to-noise ratio by selectively suppressing non-target neurons. Finally, Iyer et al. [143] demonstrated that active dendritic mechanisms enable the reception of contextual vectors and modulation of feedforward signals. When combined with a k-winner-take-all sparsity constraint, this approach improves data efficiency and effectively mitigates catastrophic forgetting.

Overall, the core of this learning rule lies in utilizing the spatial structure of dendrites to guide signal routing and integration. It emphasizes the physical isolation of different types of information (such as feedforward and feedback signals) at different locations within neurons (such as basal and parietal dendrites), or leveraging the topological structure of dendrites to achieve specific computational functions. The learning process often relies on the passive or active processing of electrical signals by this morphological structure, rather than simply on the statistical updates of synaptic weights. This learning approach can help models mitigate problems such as catastrophic forgetting and enable lifelong learning. However, it also faces limitations, such as the need to design specific neuron morphologies, increasing the difficulty of model implementation; and the requirement for additional contextual signals as input.

3.3.2. Plasticity-Based Learning Rules

These methods aim to identify fully local learning rules that do not require symmetric weights to replace BP, relying solely on pre- and post-synaptic activity together with global modulatory factors. Although some studies have demonstrated that local learning can achieve accuracy comparable to BP, many of these approaches still rely on partial forms of local information adjustment. Early research explored the training of deep networks using non-BP methods, evaluating the performance of target propagation and feedback alignment (FA) on large-scale tasks [144]. This line of work inspired Konishi et al. [145] to develop a biologically plausible learning rule based on numerical simulations of signal propagation in the mouse medial prefrontal cortex. Their approach improved FA by locally supplying error signals from focal layers, achieving learning performance comparable to BP.

Ma et al. [146] further investigated the impact of distinct local classifiers, introducing auxiliary classifiers at each layer to compute local errors. This strategy enables training without global error propagation and is particularly compatible with the characteristics of spiking neural networks. Similarly, Ororbia et al. [147] employed local error units and feedback weights to regenerate targets, updating synaptic weights by minimizing local mismatches. In parallel, local learning rules for shallow networks have been explored [148]. These rules depend exclusively on pre- and post-synaptic neuronal activity, predictive dendritic inputs, and globally broadcast modulatory signals to compute local errors. Illing et al. [149] applied such learning rules to saccade-based causal biological contrastive predictive learning scenarios, updating synaptic weights through local Hebbian mechanisms driven by contrastive signals and predictive inputs from apical dendrites. Moreover, several studies [150,151] have demonstrated that predictive coding networks can be mathematically equivalent to BP weight updates under specific conditions, while fully satisfying locality constraints. Incorporating local dendritic mechanisms further enhances predictive coding performance and broadens its applicability, enabling the training of biologically plausible spiking networks using dendritically predicted local errors [152].

Synaptic plasticity also plays a central role in biologically plausible learning. Aitchison et al. [153] observed that synapses can maintain probability distributions over weights, with higher uncertainty corresponding to higher learning rates. In this framework, learning rates are encoded through the variability of postsynaptic potentials, leading to a Bayesian interpretation of synaptic plasticity. Lin et al. [154] showed that local feedback via axon–synapse connections can approximate BP updates, eliminating the need for separate feedback networks. Kim et al. [155] analyzed heterosynaptic plasticity using mutual information theory, revealing the computational capacity of dual-input synapses.

Furthermore, synaptic competition and differential Hebbian rules have been shown to learn controller input–output structures effectively [156]. Building on these insights, Bicknell et al. [157] developed a synaptic learning rule that exploits nonlinear dendritic computation, allowing neurons to adaptively utilize active (supralinear) or passive (sublinear) dendritic nonlinearities to solve nonlinear feature-binding problems. Changes in synaptic strength can also be modulated by overall neuronal output activity [158], extending classical Hebbian learning through element-wise synaptic updates for gradient-based optimization that is robust to outliers. Since neurons exhibit multiple forms of plasticity, Wang et al. [159] proposed a synergistic plasticity rule that jointly regulates synaptic weights and intrinsic neuronal excitability, enabling adaptive reservoir dynamics.

In summary, plasticity-based learning mechanisms offer strong biological plausibility by combining local error signals with Hebbian learning principles. Because synaptic updates depend exclusively on local pre- and post-synaptic information, these approaches are particularly well suited for neuromorphic hardware implementations. Moreover, they avoid the strict separation of forward and backward phases required by conventional BP, which is critical for enabling real-time and lifelong learning. Although several methods have been shown to approximate well-defined statistical learning objectives with solid theoretical foundations, they still face challenges, including limited performance on large-scale tasks and sensitivity to hyperparameter selection.

3.3.3. Bio-Inspired Algorithm-Based Learning Rules

Single neuron models based on the nonlinear integration of dendritic branches exhibit powerful computational capabilities. Due to their low parameter count, these models are often trained using evolutionary or heuristic algorithms. These algorithms simulate biological swarm behaviors [160–162], evolutionary strategies [163,164], and natural laws [165], by encoding model parameters within a decision space and searching for optimal weights therein. Differential evolution, as a population-based global optimization method, has demonstrated robust performance and has been applied to train neural networks [96]. Yu et al. improved the information interaction mechanism between populations, further enhancing training accuracy. Researchers have employed particle swarm optimization to train dendritic neurons [161,166,167]. The algorithm records the best historical information and share them with others for search. Additionally, numerous other algorithms have been utilized for training neural networks [97,168–171]. These methods can navigate the local optima traps often encountered in BP through various search strategies, thereby achieving superior performance. However, their optimization process requires a fitness function, making them ill-suited for unsupervised learning. Furthermore, search efficiency correlates with the scale of the decision space, resulting in high computational costs for large-scale problems.

These optimization-based methods can effectively escape the local optima that often hinder backpropagation-based training by leveraging diverse global search strategies, thereby achieving competitive or superior performance in certain tasks. However, their reliance on explicit fitness functions makes them unsuitable for unsupervised learning scenarios. Moreover, optimization efficiency is strongly dependent on the dimensionality of the decision space, leading to substantial computational overhead when applied to large-scale problems.

3.4. Applications

Currently, dendritic learning remains in its infancy, with most research focused on testing performance and method feasibility on benchmarks such as the UCI Database and MNIST. While its performance still faces challenges, there are also several successful application cases. In this section, we introduce and discuss the applications of dendritic learning in image classification, image segmentation, time-series prediction, etc. Table 2 lists the applications of dendritic learning.

Table 2. Summary of representative applications of dendritic learning.

Applications	Dendritic Advantages
Benchmarks [102,172,173]	Flexible integration with deep learning frameworks, leading to improved classification accuracy.
Remote sensing [174]	Flexible integration of multi-level feature maps, effective noise suppression, and improved change detection performance.
Ultrasound image segmentation [175]	Nonlinear excitation–inhibition mechanisms in dendritic computation enable adaptive feature aggregation and boundary optimization.
CT image segmentation [176,177]	Improved capture of local features at the channel level through dendritic integration.
Environmental prediction [178,179]	Robust modeling of nonlinear temporal dependencies in environmental time-series data.
Wind power forecasting [180]	Enhanced prediction accuracy under highly stochastic and nonstationary conditions.
Energy systems [98]	Efficient multivariate forecasting using a single quaternion-based dendritic model.
Financial forecasting [181,182]	Lightweight single-neuron models enabling efficient and accurate financial time-series prediction.

3.4.1. Classification Tasks

A single dendritic neuron has demonstrated remarkable capabilities in certain text or tabular classification tasks [84,87,103,183]. Constrained by the computational capacity of single neurons, researchers have integrated dendritic learning with existing deep learning approaches to tackle complex image classification problems. These approaches leverage dendrites' nonlinear fitting capabilities to enhance models' decision-making power in intricate feature spaces. Wang et al. [102] pioneered the integration of dendritic learning with convolutional networks. This method employs deep networks for image feature extraction, with dendritic learning serving as the classifier. Results demonstrate that incorporating dendritic learning effectively improves classification accuracy. Building upon this foundation, subsequent studies expanded its application scope to tackle complex medical images. Furthermore, transformer models achieved tremendous success as the foundation for LLMs. Consequently, Zhang et al. [172] pioneered the integration of dendritic learning with Transformers for image classification, demonstrating its superiority. Xu et al. [173] leveraged dendritic learning to refine attention mechanisms, enabling better capture of nonlinear relationships and outstanding performance in image classification. Similarly, dendritic-based Transformers have been applied to retinal disease detection. Differing from the above approaches, Zhang et al. [174] employed dendritic learning for change detection in remote sensing imagery.

3.4.2. Image Segmentation

Owing to the inherent nonlinear processing capabilities of dendrites, dendritic learning is well suited for image segmentation tasks, which often involve challenges such as blurred boundaries and complex target regions. Several studies have shown that dendritic learning can effectively address these issues [184–186].

For example, Zhang et al. [175] proposed dendritic convolutional kernels to capture nonlinear feature interactions, thereby enhancing segmentation accuracy. Liu et al. [176] introduced dilated dendritic learning to model both local and global representations for medical image segmentation. Zhong et al. [177] further leveraged dendritic integration mechanisms to achieve multi-scale segmentation of medical images.

3.4.3. Time-Series Forecasting

Due to the prevalence of temporal forecasting tasks in real-world applications, dendritic learning has been widely applied to time-series prediction problems [23,187,188]. In environmental and energy engineering, dendritic learning has been used for tasks such as PM 2.5 concentration prediction [178], wind power forecasting [180], and photovoltaic power forecasting [179]. In addition, applications have been reported in financial and tourism forecasting [181,182]. Notably, Yu et al. [98] proposed a quaternion-based dendritic model to address multivariate financial time-series forecasting problems. Overall, dendritic learning demonstrates robust predictive performance in forecasting tasks. When combined with phase space reconstruction techniques, lightweight single-branch dendritic models can achieve highly accurate predictions [189].

4. Challenges & Future Directions

Dendritic learning is still in an early yet rapidly evolving stage of development, and several key challenges remain. These challenges can be broadly summarized into four categories: scalability and network depth, limitations of learning algorithms, performance limitation, and hardware and implementation complexity. Many existing dendritic models (e.g., DNM) are fundamentally single neuron–based architectures. Although individual dendritic neurons possess strong nonlinear computational capabilities, relying primarily on single neurons makes it difficult to address complex multiclass classification problems or large-scale datasets [104]. Extending these models to larger systems introduces significant optimization difficulties in high-dimensional parameter spaces [88, 190]. Furthermore, many dendritic models trained by BP suffer from well-known issues such as sensitivity to initialization, susceptibility to local optima, and slow convergence. More importantly, BP is biologically implausible due to its reliance on symmetric weight transport and globally propagated error signals. Many existing biologically inspired models still depend on unrealistic global signals [109,114,142]. In addition, dendritic learning models currently lag behind highly optimized conventional deep neural networks when tackling extremely complex tasks [119,120]. While gradient-based AI models benefit from efficient GPU acceleration, dendritic learning often incurs substantial computational overhead due to non-gradient optimization and the simulation of detailed biophysical mechanisms, such as multi-compartment structures and ion-channel dynamics. These factors significantly hinder large-scale deployment on conventional hardware [49,191]. Although neuromorphic hardware provides promising low-power alternatives, the ecosystem for dendritic-specific computation remains underdeveloped [120].

To address these challenges, several promising research directions can be identified, including architectural innovation, advanced learning algorithms, hardware implementation, and theoretical expansion and application development. First, exploring dendritic learning–based neuronal architectures for constructing deeper networks may help enhance performance on complex tasks by embedding dendritic isolation and intrinsic nonlinear processing into network design. Second, incorporating structural plasticity and dynamic morphological mechanisms could enable adaptive pruning and topology reconfiguration during training, extending learning beyond static weight optimization. Third, further investigation into dendrite-local learning mechanisms may contribute to the development of more biologically plausible learning rules that alleviate some limitations of backpropagation and support online or continual learning. However, their robustness and effectiveness at scale require further validation. Fourth, translating trained dendritic models into logic-circuit representations offers a promising direction, particularly for deployment on resource-constrained edge devices, where ultra-fast inference and low power consumption are critical. Meanwhile, developing efficient training pipelines, potentially leveraging GPU acceleration or hybrid analog–digital computation, is essential for improving scalability. Finally, strengthening the theoretical foundations of dendritic learning, particularly with respect to interpretability and generalization, and expanding its application domains remain crucial steps toward advancing dendritic learning into a mature and impact AI paradigm.

5. Conclusions

This paper provides a comprehensive review of the neuroscience foundations of dendritic learning, its neural architectures, learning rules, activation functions, and applications across diverse domains such as image classification, image segmentation, and time series prediction. Additionally, we review dendritic learning architectures including single-dendrite neurons, bio-inspired architectures, spiking dendritic architectures, and interpretable architectures. We further highlight the biologically unexplainable limitations of BP learning and review dendritic learning rules, encompassing morphology-based, plasticity-based, and bio-inspired learning rules. Finally, this survey discusses the advantages and disadvantages of dendritic learning across diverse application domains.

This paper is intended for researchers in the fields of neural networks and artificial intelligence. Scholars engaged in related research can leverage the findings summarized herein to deepen existing studies and understand the importance and necessity of dendritic learning, laying a solid foundation for advancing research and driving the next generation of bio-inspired trustworthy artificial intelligence.

Author Contributions

Z.L.: conceptualization, methodology, writing—original draft preparation; W.G.: visualization, investigation; S.G.: supervision,writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

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Use of AI and AI-Assisted Technologies

During the preparation of this work, the author used ChatGPT to enhance grammatical correctness and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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