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A Survey of Deep Learning Architectures in Modern Machine Learning Systems: From CNNs to Transformers

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Abstract: Deep learning has become a cornerstone of modern machine learning systems, empowering breakthroughs across domains such as computer vision, natural language processing, speech recognition, and autonomous control. This survey provides a comprehensive overview of the evolution, design principles, and application of deep learning architectures, with a particular focus on Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based models. We begin by tracing the historical development of neural architectures, highlighting the shift from spatial and temporal encoders to attention-driven models that enable long-range dependency modeling and cross-modal learning. We then present a detailed analysis of architectural components, including convolutional layers, recurrent units, self-attention mechanisms, normalization techniques, and position encoding strategies, emphasizing their mathematical foundations and design trade-offs. Furthermore, we explore the deployment of these architectures in diverse domains, illustrating real-world use cases and performance comparisons through visual diagrams. The survey also identifies major challenges in current deep learning systems-such as interpretability, data efficiency, scalability, and ethical deployment-and outlines promising directions including federated learning, parameter-efficient fine-tuning, biologically inspired computation, and unified multimodal frameworks. By synthesizing the architectural trajectory from CNNs to Transformers, this survey aims to guide researchers and practitioners in selecting, adapting, and advancing deep learning models to meet the evolving demands of real-world machine learning applications. Our findings highlight both the robustness and limitations of current approaches, offering insights into the next generation of intelligent and adaptable systems.

Keywords: Deep Learning, Machine Learning Architectures, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs)

1. Introduction

Deep learning has become the cornerstone of modern machine learning systems, enabling unprecedented performance across a wide range of tasks including computer vision, natural language processing, speech recognition, and decision-making. As a subfield of machine learning inspired by the hierarchical structure of the human brain, deep learning utilizes multilayered artificial neural networks to automatically extract increasingly abstract representations from data. Since the landmark success of convolutional neural networks (CNNs) on the ImageNet Large Scale Visual Recognition Challenge in 2012, deep learning has undergone remarkable evolution in both architectural design and application scope [1]. The early dominance of CNNs in image-related tasks was soon complemented by the development of recurrent neural networks (RNNs) and their variants, which became central to sequence modeling. However, the introduction of the Transformer architecture in 2017 marked a paradigm shift by replacing recurrence with self-attention, enabling greater parallelism and performance scaling across modalities [2]. These advances have not only improved benchmark results but also triggered the emergence of foundation models-large-scale pretrained networks with generalization capabilities across diverse tasks.

At the heart of this progression lies the synergy between algorithmic innovation, computing infrastructure, and data availability. The increasing complexity and depth of neural networks have been supported by advances in hardware accelerators such as GPUs, TPUs, and neuromorphic chips, as well as distributed training frameworks like Horovod and DeepSpeed [3]. Simultaneously, the accessibility of massive datasets such as ImageNet, COCO, OpenWebText, and Common Crawl has made it feasible to train large-capacity models capable of capturing complex data distributions. This convergence has led to the rise of architectures like ResNet, DenseNet, EfficientNet, LSTM, GRU, Transformer, BERT, and Vision Transformers (ViT), each addressing specific limitations in representational power, training efficiency, or scalability. While earlier architectures relied heavily on hand-designed features and inductive biases such as local connectivity or temporal recurrence, recent trends favor flexible, scalable, and attention-based mechanisms capable of capturing long-range dependencies and contextual interactions across modalities [4]. In particular, the Transformer and its derivatives have become the default backbone for many state-of-the-art models in both vision and language tasks, due to their modularity, scalability, and compatibility with large-scale pretraining.

Despite these achievements, the proliferation of deep learning architectures presents several challenges in terms of interpretability, generalization, robustness, and efficiency. Model depth and complexity often lead to overfitting, vanishing gradients, or exploding computational costs, necessitating innovations such as batch normalization, residual connections, knowledge distillation, and pruning [5]. Furthermore, the deployment of deep models in resource-constrained environments such as mobile devices, edge computing nodes, or embedded systems has driven the development of lightweight variants such as MobileNet, SqueezeNet, and TinyBERT. On the other hand, foundation models like GPT-4, PaLM, and SAM exhibit emergent abilities, but raise concerns regarding transparency, bias amplification, environmental cost, and data privacy [6]. Therefore, understanding the architectural design principles, trade-offs, and historical evolution of deep learning systems is essential for researchers and practitioners seeking to develop reliable and efficient AI applications.

This survey aims to provide a structured and in-depth review of deep learning architectures in modern machine learning systems, with a particular emphasis on the transition from CNN-based to Transformer-based models. We conclude by outlining emerging trends in deep learning architecture, including sparse attention, mixture-of-experts, neural architecture search, and biologically inspired design. Through this comprehensive analysis, we aim to provide insights into the architectural foundations that have shaped the current landscape of deep learning and to inform future developments in scalable and efficient machine learning systems.

2. Architectural Foundations

The evolution of deep learning architectures over the past decade has been marked by increasingly sophisticated designs that aim to enhance representational power, training stability, and computational efficiency. Convolutional Neural Networks (CNNs) represent the earliest breakthrough architecture that demonstrated deep learning's potential, particularly in visual recognition tasks. A CNN is characterized by its use of local receptive fields, weight sharing, and spatial hierarchies to extract low-to-high level features from image data. The foundational LeNet-5 model pioneered the concept of hierarchical feature extraction, while the AlexNet architecture demonstrated the feasibility of deep CNNs trained on large-scale datasets with GPU acceleration [7]. Subsequently, models such as VGGNet emphasized depth by stacking more convolutional layers with uniform kernel sizes, leading to improved performance at the cost of higher computational demands. ResNet introduced the concept of residual connections to mitigate the vanishing gradient problem in deep networks, enabling architectures with over a hundred layers to be trained effectively by learning residual mappings rather than direct transformations [8]. Further innovations like DenseNet added dense connectivity between layers, enhancing feature reuse and gradient flow, while EfficientNet proposed a principled scaling strategy balancing depth, width, and resolution to achieve state-of-the-art performance with fewer parameters [9].

Parallel to CNNs, Recurrent Neural Networks (RNNs) emerged as a dominant paradigm for sequential data modeling. Traditional RNNs suffer from difficulties in capturing long-term dependencies due to gradient vanishing or explosion. To address this, Long Short-Term Memory (LSTM) networks were introduced, incorporating memory cells and gating mechanisms to preserve long-range information across sequences [10]. Gated Recurrent Units (GRUs) provided a simpler alternative with comparable performance, reducing the number of gates while maintaining the ability to learn time-dependent patterns. RNN-based models became the backbone for applications in language modeling, machine translation, speech recognition, and time-series forecasting. However, sequential processing inherently limited parallelism, leading to inefficiencies in training and inference on long sequences. This bottleneck spurred the exploration of attention mechanisms, which enable the model to selectively focus on relevant parts of the input regardless of position. The introduction of the Transformer architecture represented a significant departure from both convolutional and recurrent paradigms by relying entirely on self-attention mechanisms and positional encodings, enabling full parallelization across sequence elements and superior scalability [11].

Transformers, initially proposed in the context of natural language processing via the "Attention is All You Need" paper, became the foundation for a wave of powerful language models. The encoder-decoder structure, composed of multi-head attention and feedforward sublayers, allows for contextualized token representations across entire sequences. BERT (Bidirectional Encoder Representations from Transformers) demonstrated the power of bidirectional context and pretraining via masked language modeling, setting new benchmarks in question answering, sentiment analysis, and named entity recognition [12]. On the generative side, GPT (Generative Pretrained Transformer) adopted an autoregressive formulation, producing fluent text across diverse topics and later evolving into multi-billion parameter foundation models such as GPT-3 and GPT-4. T5 (Text-to-Text Transfer Transformer) unified all NLP tasks under a text-to-text framework, while models like XLNet, RoBERTa, and ALBERT explored pretraining objective variants, architectural optimizations, and parameter sharing. Beyond language, Vision Transformers (ViT) extended the Transformer architecture to image understanding by treating images as sequences of flattened patches, achieving competitive accuracy with CNNs on classification tasks when pretrained on large datasets [13].

Hybrid architectures have also gained traction, combining the strengths of CNNs and Transformers or augmenting them with auxiliary modules. For example, models like DETR (DEtection TRansformer) and Swin Transformer integrate convolutional backbones with Transformer-based attention for object detection and dense prediction. In speech processing, models such as Conformer blend convolutional modules with Transformer blocks to capture both local and global dependencies. Graph Neural Networks (GNNs) represent another emerging architecture that generalizes neural operations to non-Euclidean data such as graphs, allowing relational reasoning in molecular property prediction, social networks, and recommender systems [14]. These architectural

advances are increasingly unified under the trend of pretraining large-scale models on diverse data modalities followed by task-specific fine-tuning. This paradigm, often referred to as transfer learning or foundation model scaling, reduces the need for labeled data and enables few-shot or zero-shot generalization to new tasks.

In addition to performance improvements, deep learning architecture design increasingly emphasizes training efficiency, modularity, and deployment feasibility. Techniques such as neural architecture search (NAS) automate the discovery of optimal architectures under hardware constraints, leading to models like NASNet and EfficientNet that outperform manually designed networks. Knowledge distillation transfers knowledge from large teacher models to compact student models, allowing lightweight deployment without significant performance loss. Quantization, pruning, and low-rank approximation further reduce model size and latency, enabling deployment on edge devices and real-time systems. These efforts are critical as deep learning continues to expand into industrial and consumer applications where compute and memory are limited. Simultaneously, concerns around interpretability and trust have led to the development of inherently explainable architectures or modules that allow visualization of attention maps, saliency gradients, or concept activations, offering insights into model behavior and decision logic [15].

The architectural trajectory from CNNs and RNNs to Transformer-based models reflects a broader shift in machine learning toward scalability, generality, and data-centric design. While CNNs and LSTMs remain highly effective for domain-specific problems with strong inductive biases such as locality or temporality, Transformers have demonstrated that minimal architectural assumptions combined with massive pretraining can achieve robust performance across tasks and modalities. However, this comes with trade-offs in terms of computational requirements, environmental impact, and interpretability. As such, architecture design in deep learning is evolving toward adaptable, efficient, and ethical systems that balance performance with transparency and sustainability.

3. Applications Across Domains

The widespread adoption of deep learning architectures has led to transformative applications across a multitude of domains,from vision and language to biomedicine,autonomous systems,and financial forecasting.These architectures,particularly CNNs,RNNs,and Transformers,have been adapted and optimized to accommodate the structural and functional needs of each application area,often resulting in hybrid or specialized variants that achieve domain-specific state-of-the-art results.In the domain of computer vision,convolutional neural networks have long served as the backbone for tasks such as image classification,object detection,semantic segmentation,and instance recognition.Architectures such as ResNet,Inception,and EfficientNet continue to dominate benchmarks like ImageNet,COCO,and Cityscapes due to their hierarchical feature extraction and spatial inductive biases[16].The introduction of Vision Transformers(ViT)disrupted the CNN-dominated landscape by demonstrating that self-attention-based models can achieve comparable or superior performance when sufficient pretraining data and compute are available.Hybrid models like Swin Transformer further enhance performance by integrating local attention with hierarchical representations.These vision-specific architectures are visualized as part of the deep learning model workflow in Figure 1,which illustrates how raw image inputs are transformed through convolutional or attention layers into structured representations,which are subsequently used for classification,detection,or generation tasks.

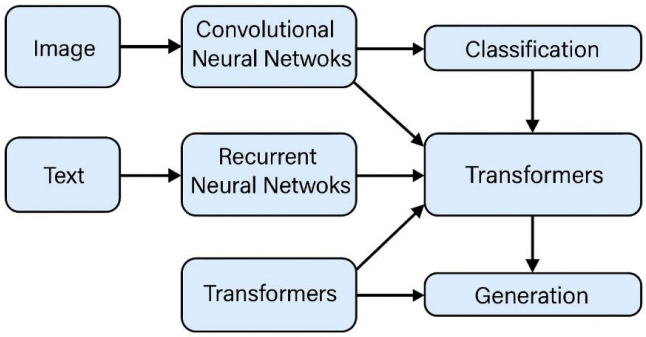

Figure 1. Workflow of deep learning models in vision and language.

In natural language processing,the transition from RNN-based architectures to Transformer-based models has been particularly impactful.Early approaches such as LSTMs and GRUs powered language modeling,sentiment classification,and machine translation,but struggled with long-range dependencies and limited parallelism.The introduction of the Transformer architecture and the pretraining-finetuning paradigm enabled massive improvements in language understanding and generation.BERT-like models provide bidirectional contextual embeddings that are fine-tuned for downstream tasks,while GPT-like models offer autoregressive generation capabilities,enabling coherent text synthesis,summarization,translation,and dialogue.Language models such as T5,XLNet,and RoBERTa introduced variations in training objectives and architectures to improve generalization,robustness,and training efficiency[17].These architectures have been incorporated into digital assistants,search engines,content moderation systems,and even legal and medical document review pipelines.In speech processing,models like DeepSpeech,wav2vec,and Conformer combine convolution,recurrence,and attention mechanisms to enable end-to-end speech recognition,speaker identification,and emotion detection.In real-time conversational AI,Transformer-based architectures underpin systems such as ChatGPT and Bard,which leverage reinforcement learning with human feedback(RLHF)to align generated content with human preferences[18].

Beyond vision and language,deep learning has been deployed in biomedical domains for tasks such as protein folding,drug discovery,medical image segmentation,and patient outcome prediction.CNNs are widely used for analyzing radiology images including CT,MRI,and X-rays,where models like U-Net and its variants perform pixel-level segmentation for tumor detection or organ delineation.Transformers have

recently been adapted to non-Euclidean biomedical data;for example,AlphaFold2 employs attention mechanisms to predict 3D protein structures from amino acid sequences with remarkable accuracy[19].In genomics,RNNs and attention-based models are used for DNA sequence classification,gene expression modeling,and CRISPR target prediction.In clinical natural language processing,BERT-based models such as BioBERT and ClinicalBERT are fine-tuned on medical corpora to extract clinical entities,relations,and events from electronic health records.Figure 2 illustrates a high-level taxonomy of deep learning applications across major domains,categorizing models and tasks by data modality and output objective.This visual framework demonstrates how architectural choices are influenced by domain constraints such as input structure,latency requirements,interpretability demands,and annotation availability.

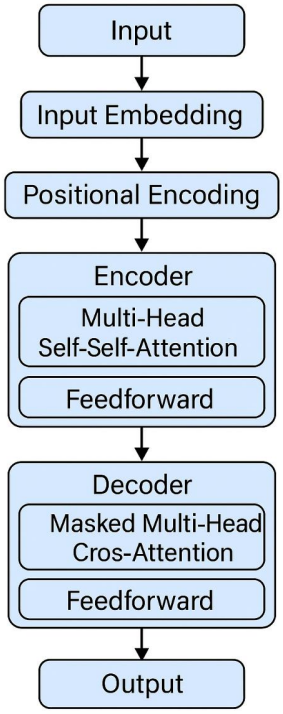

Figure 2. Taxonomy of deep learning applications across domains.

In autonomous systems such as self-driving vehicles and drones,deep learning enables perception,localization,planning,and control.CNNs and object detection networks like YOLO and Faster R-CNN are employed for identifying road users and obstacles,while RNNs and attention-based models process temporal data from sensors for trajectory prediction and decision-making.Reinforcement learning combined with deep networks(i.e.,deep Q-networks and policy gradients)facilitates autonomous control in simulated and real-world environments.Transformer-based scene encoders and behavior prediction models enhance multi-agent coordination in traffic systems[20].In robotics,deep learning is applied to vision-based grasping,language-guided navigation,and tactile feedback interpretation.These models are increasingly deployed at the edge,requiring architectural efficiency and robustness to environmental noise.Similarly,in finance and econometrics,recurrent and attention-based models are used for stock price prediction,fraud detection,credit scoring,and portfolio optimization.Time series models augmented with attention mechanisms provide better interpretability and dynamic feature weighting compared to traditional statistical methods.Deep learning is also central to recommender systems,where sequential recommendation benefits from RNNs and Transformers to model evolving user preferences across clickstreams,purchase history,and social context[21].

In multimodal applications,architectures capable of processing and fusing inputs from different modalities have become increasingly important.Models such as CLIP(Contrastive Language-Image Pretraining)align visual and textual representations for zero-shot image classification,while Flamingo and GPT-4V combine language and vision capabilities to answer questions about images or generate image captions.Multimodal Transformers jointly attend to visual and textual sequences,enabling complex reasoning across data types.In the medical field,such models can process both imaging data and clinical narratives to improve diagnosis or prognosis.Other applications include visual question answering,image-grounded dialogue,and audio-visual scene understanding.This trend highlights the growing demand for flexible architectures that can operate across modalities and adapt to heterogeneous data environments.Meanwhile,deployment considerations such as model size,inference latency,and privacy constraints continue to influence architectural design.Lightweight models are essential for mobile health monitoring,embedded vision in IoT devices,and smart home assistants.Techniques such as knowledge distillation,pruning,and quantization enable real-time inference without significant loss in accuracy.

Across domains,the architecture of choice is often dictated by a combination of data characteristics,task requirements,and operational constraints.While CNNs remain dominant in spatially structured data such as images,Transformers are increasingly favored for tasks requiring global context,sequence modeling,and cross-modal understanding.The integration of these architectures into hybrid systems is common,combining inductive priors with flexible attention mechanisms.Furthermore,foundation models pretrained on large-scale corpora are often adapted for domain-specific tasks via fine-tuning or parameter-efficient adaptation methods such as adapters and low-rank reparameterization.As shown in Figures 1 and 2,the evolution of deep learning architectures has not only advanced theoretical capabilities but also reshaped practical workflows across sectors.In the next section,we examine the key challenges encountered in designing,training,and deploying these architectures at scale,and discuss ongoing research directions that aim to address limitations in efficiency,interpretability,fairness,and generalization.

4. Challenges and Research Trends

Despite the remarkable progress made in the development and deployment of deep learning architectures, significant challenges remain that constrain their scalability, interpretability, efficiency, and trustworthiness. As models

grow in depth and parameter count, the computational demands for training and inference have escalated exponentially, raising concerns about the environmental impact, resource inequality, and latency constraints associated with large-scale deep learning systems. The training of foundation models such as GPT-3, PaLM, and LLaMA involves thousands of GPUs running for weeks, consuming millions of kilowatt-hours of electricity and incurring costs inaccessible to most academic or small industry research groups [22]. To address this, research has focused on model compression techniques including pruning, quantization, knowledge distillation, and low-rank decomposition, which aim to reduce parameter counts and floating-point operations without significant performance degradation. Lightweight architectures such as MobileNetV3, TinyBERT, and DistilGPT are increasingly deployed in edge and embedded contexts, where power and memory constraints preclude the use of large models. At the same time, techniques such as parameter-efficient fine-tuning, LoRA (Low-Rank Adaptation), and adapter modules allow for effective downstream task adaptation without full-model retraining, enabling scalable model deployment across devices and applications [23].

Another persistent challenge is the interpretability and explainability of deep neural networks, which often function as opaque black boxes with limited insight into their internal decision processes. While visualization techniques such as saliency maps, attention heatmaps, and feature activation tracking provide some understanding of what parts of the input influence model predictions, these tools remain limited in scope, robustness, and user interpretability. In safety-critical domains such as healthcare, autonomous driving, and legal decision-making, lack of transparency undermines user trust and limits regulatory compliance. To address this, inherently interpretable models, post-hoc explanation frameworks like LIME and SHAP, and concept-based interpretability approaches are being actively explored [24]. In the case of Transformer-based models, attention weights were initially interpreted as explanations, but subsequent studies showed that attention distributions do not always align with causal influence. As a result, attribution methods that combine gradient-based signals and causal analysis are gaining traction. Furthermore, the field of explainable AI (XAI) is expanding toward creating interaction-based explanation systems that allow domain experts to query, simulate, and intervene in model behavior, moving beyond static explanations toward dynamic interpretability [25].

Generalization and robustness constitute another major frontier in deep learning research. Although large models achieve impressive performance on benchmark datasets, they often suffer from poor generalization to out-of-distribution (OOD) data, vulnerability to adversarial examples, and performance degradation under domain shift. For instance, minor perturbations in input images can cause high-confidence misclassifications, while deployment in real-world settings often reveals biases and blind spots that were absent in the training data. Research into adversarial training, data augmentation, and uncertainty estimation has aimed to improve robustness, while techniques such as test-time adaptation and domain generalization seek to enhance model performance in unseen environments [26]. Self-supervised learning, particularly contrastive learning and masked prediction objectives, has emerged as a promising approach to pretrain models that are less reliant on annotated data and more robust to noise. In addition, curriculum learning and active learning are employed to improve sample efficiency and mitigate overfitting in low-resource settings. Robustness also includes dealing with noisy labels, missing data, and multimodal inconsistencies, all of which are common in real-world applications and require architectures capable of handling uncertainty and partial observability.

Fairness, accountability, and bias mitigation are growing areas of concern in deep learning system deployment. Numerous studies have shown that deep models can amplify historical biases present in the training data, leading to discriminatory outcomes in facial recognition, hiring algorithms, credit scoring, and predictive policing. These biases often stem from imbalanced datasets, spurious correlations, or lack of demographic representation. Research into fairness-aware learning algorithms aims to incorporate fairness constraints during training, measure disparate impact across groups, and mitigate unintended model behavior through regularization or debiasing [27]. Federated learning frameworks have also been proposed to enable decentralized training across user devices while preserving data privacy, but they introduce new challenges such as client drift, heterogeneous data distributions, and secure aggregation. Furthermore, regulatory frameworks such as the EU AI Act and U.S. NIST AI Risk Management Framework are beginning to formalize expectations around fairness, transparency, and accountability in AI systems. Deep learning architectures must adapt to these emerging norms by incorporating compliance monitoring, ethical auditing, and provenance tracking into the model lifecycle.

Another active area of research is neural architecture search (NAS), which automates the discovery of optimal model topologies under specified constraints. Traditional architecture design is a manual, trial-and-error process that often relies on expert intuition and empirical tuning. NAS systems, by contrast, use reinforcement learning, evolutionary algorithms, or gradient-based methods to explore vast design spaces and generate architectures that balance accuracy, efficiency, and deployment cost. Early NAS approaches were computationally expensive, but recent advances such as differentiable architecture search and one-shot NAS have significantly reduced the search time and resource footprint [28]. NAS has led to the development of architectures such as NASNet, AmoebaNet, and EfficientNet, which have outperformed manually designed models on several tasks. Moreover, hardware-aware NAS methods take into account inference latency, memory usage, and energy consumption on target platforms, making it feasible to deploy customized deep learning architectures on mobile, edge, or FPGA-based systems.

Multi-modal and cross-domain learning present further architectural and training challenges. Deep learning systems are increasingly expected to process and integrate information from heterogeneous data sources such as text, images, audio, and structured metadata. Designing unified architectures that can align representations across modalities and generalize to

novel combinations of inputs requires novel fusion mechanisms, cross-modal attention layers, and contrastive alignment losses. Models like Flamingo, Gato, and Perceiver IO aim to provide universal interfaces across tasks and modalities, yet training such models remains computationally intensive and data-hungry. In the same vein, prompt-based learning and instruction tuning have emerged as lightweight alternatives for aligning model behavior across tasks without extensive fine-tuning. However, prompt engineering remains largely empirical and lacks theoretical foundations, prompting research into more structured and semantically grounded methods of conditioning large models. Another area of interest is continual learning, where models must adapt to new tasks or data distributions without catastrophic forgetting. This is particularly relevant in online and streaming scenarios, where data evolves over time, and models must be updated incrementally while retaining past knowledge [29].

Looking forward, biologically inspired deep learning models represent a long-term research vision that aims to bridge the gap between artificial neural networks and human cognition. Concepts such as spiking neural networks, neuromodulation, hierarchical temporal memory, and brain-like energy efficiency are being explored to develop systems that are more adaptive, resilient, and interpretable. At the same time, theoretical understanding of deep learning remains limited, with open questions around generalization bounds, implicit regularization, loss landscape geometry, and representation learning dynamics. Advancing these theoretical foundations is essential to designing architectures that are not only empirically powerful but also well-understood and principled. Lastly, sustainability has become a pressing consideration. The carbon footprint of training large AI models is substantial, prompting calls for standardized reporting of energy use, carbon emissions, and efficiency metrics. Techniques such as early stopping, progressive training, hardware-aware pruning, and green AI benchmarking are beginning to emerge as part of a broader shift toward responsible AI development [30]. These research directions signal a future where deep learning architectures are not only more capable and efficient, but also more accountable, inclusive, and aligned with human and environmental values.

5. Conclusion and Future Directions

The past decade has witnessed a remarkable transformation in the field of machine learning, driven by the rapid evolution of deep learning architectures from early convolutional and recurrent networks to powerful Transformer-based models capable of scaling across modalities, tasks, and domains. This paper has presented a comprehensive survey of these architectural developments, highlighting the design principles, performance characteristics, and domain-specific adaptations of CNNs, RNNs, and Transformers, while also drawing attention to emerging hybrid and modular architectures that combine the strengths of multiple paradigms. From the hierarchical spatial encoding of CNNs that revolutionized visual recognition, to the temporal sequence modeling capabilities of LSTMs and GRUs, to the attention-based contextual representations enabled by Transformers in language and vision, each successive innovation has expanded the frontiers of what machine learning systems can perceive, infer, and generate. These architectures have been deployed across an increasingly diverse set of applications including computer vision, natural language processing, speech recognition, biomedical data analysis, autonomous control, financial modeling, and multimodal fusion, demonstrating their versatility and transformative potential. However, with these advances come new challenges-ranging from the environmental cost and inefficiency of large-scale training, to concerns about fairness, interpretability, and robustness in deployment. Researchers and engineers are actively addressing these issues through compression techniques, architecture search, parameter-efficient adaptation, explainability frameworks, and ethical design practices. At the same time, nascent directions such as biologically inspired computing, continual learning, and unified multimodal architectures offer promising paths toward building next-generation models that are not only powerful but also adaptable, accountable, and sustainable. As deep learning continues to scale and integrate with real-world systems, understanding the architectural foundations that underpin its success remains essential. This survey has aimed to clarify the architectural trajectory from CNNs to Transformers, synthesize the innovations that have shaped modern machine learning systems, and illuminate the future research landscape where efficiency, generalization, and trustworthiness will define the next wave of progress. The continued evolution of deep learning architectures will not only depend on engineering ingenuity and computational power, but also on our ability to align technical systems with human values, institutional goals, and the long-term demands of global-scale deployment.

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