

A Comprehensive Review on Neural Network Architectures

Y. Angeline Christobel¹, R. Jaya Suji²

¹Dean, School of Computational Studies, Hindustan College of Arts & Science, Chennai-603103,
Email: angelinechristobel5@gmail.com

²Assistant Professor, Department of Computer Science, Hindustan College of Arts & Science, Chennai-603103, Email: jayasuji1981@gmail.com

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ABSTRACT

Deep Learning (DL), a vital element of the Fourth Industrial Revolution (4IR) or Industry 4.0 takes a leading position in the realms of machine learning (ML) and artificial intelligence (AI). Rooted in the foundation of artificial neural networks (ANN), DL technology has emerged as a pivotal force in contemporary computing. Its capacity to learn from data has rendered it a prominent subject of discussion, finding extensive applications across diverse sectors such as healthcare, visual recognition, text analytics, cybersecurity, and beyond. Nevertheless, crafting a suitable DL model presents a formidable challenge. The challenge stems from the dynamic nature and intrinsic variations present in real-world problems and datasets. Adapting DL to address the intricacies of these challenges requires careful consideration and innovative approaches. As DL continues to shape the technological landscape, its ability to transform industries and address complex problems is becoming increasingly evident. In this paper, we explore into the architecture and feature of Artificial Neural Network(ANN), Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN).

Keywords: Machine Learning(ML), Deep Learning(DL), Artificial Neural Networks(ANN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN)

1. INTRODUCTION

Deep Learning (DL) constitutes a specialized branch within machine learning (ML), centering on the creation and utilization of artificial neural networks for addressing intricate challenges. It draws inspiration from the structure and functioning of the human brain, attempting to mimic the way humans learn and make decisions. Deep Learning has gained immense popularity and success in recent years, primarily due to its ability to automatically learn hierarchical representations from data. Deep learning centers on artificial neural networks (ANNs), comprising interconnected nodes or artificial neurons structured into layers. These layers typically encompass an input layer, one or more hidden layers, and an output layer. The connections between nodes are assigned weights, and the learning process involves adjusting these weights during training. Deep learning focuses on the utilization of deep neural networks, characterized by multiple hidden layers. These networks excel at learning hierarchical representations of data, enabling the capture of intricate patterns and features. The term "deep" refers to the number of layers in the network. During training, labeled data is fed into the neural network, and iterative adjustments to connection weights are made to minimize the disparity between predicted and actual outputs. This adjustment process employs optimization algorithms and backpropagation, a method that updates weights based on the error signal. Deep learning excels in feature representation learning, facilitating the automatic extraction of pertinent features from raw data. The hierarchical representation empowers the network to grasp intricate features across various levels of abstraction. This methodology has showcased notable success in diverse applications such as Computer Vision, Natural Language Processing (NLP), and Speech Recognition. Healthcare, Autonomous Vehicles, and Finance. As deep learning continues to evolve, researchers explore techniques such as transfer learning, reinforcement learning, and the development of more interpretable architectures. The integration of deep learning with other AI approaches, such as symbolic reasoning, is also an area of active research. The field holds immense promise for solving complex problems across various domains, driving innovation and advancements in artificial intelligence. This paper examines the structures and characteristics of various neural networks.

2. LITERATURE REVIEW

In [1], the authors meticulously examined the advantages, drawbacks, and diverse applications of deep learning algorithms within the healthcare domain. Zengchen Yu et al. [2] delved into the theoretical explanation, developmental history, and applications of deep learning algorithms specifically in disease prediction. Their analysis not only scrutinized existing deficiencies in disease prediction but also proposed contemporary solutions.

Alzubaidi et al. [3] provided a comprehensive outline underscoring the significance of deep learning (DL) and elucidating various types of DL techniques and networks. The focus was on Convolutional Neural Networks (CNNs), the most widely employed DL network type. The authors meticulously detailed the evolution of CNN architectures, emphasizing their key features. Additionally, they outlined challenges encountered in the field of disease prediction and suggested potential solutions, thereby contributing to a clearer understanding of existing research gaps.

In [4], the author consolidated practical domains where the effectiveness of deep learning techniques becomes evident. Frank Emmert-Streib et al. [5] provided an introductory review covering a range of deep learning methodologies, including Deep Feedforward Neural Networks (DFFNN), Convolutional Neural Networks (CNNs), Deep Belief Networks (DBNs), Autoencoders (AEs), and Long Short-Term Memory (LSTM) networks.

Ajay Shrestha and Ausif Mahmood [6] conducted a review focusing on optimization methods to enhance training accuracy and reduce training time in deep learning models. They elucidated the mathematical foundations behind training algorithms utilized in recent deep networks and shed light on both existing limitations and potential improvements.

Maximilian Pichler et al. [7] provided an extensive review of machine learning (ML) and deep learning (DL), covering historical advancements, algorithmic categories, differences from conventional statistical techniques, and overarching principles. Their exploration extended to areas where ML and DL models demonstrate proficiency in predictive tasks, suggesting alternative methodologies to classical statistical approaches for inference. Additionally, they underscored emerging trends like scientific and causal ML, explainable AI, and responsible AI, emphasizing their potential implications for ecological data analysis.

In [8], the researchers classified deep learning techniques into supervised, unsupervised, reinforcement, and hybrid learning-based models. Zhiying Hao [9] offered an elucidation of deep learning concepts, outlining their merits, drawbacks, and practical applications. Ambuj Mehrish et al. [10] delivered a thorough examination of essential deep learning models and their utilization in speech-processing assignments. They delved into challenges within the domain and envisioned forthcoming directions, underscoring the necessity for more parameter-efficient, interpretable models and the promising role of deep learning in multimodal speech processing.

3. Neural Network Architectures

Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs) form the fundamental structure of deep learning, drawing inspiration from the organization and functioning of the human brain. Comprising interconnected nodes, or neurons, arranged in layers, ANNs possess the ability to learn intricate patterns and representations from data, rendering them versatile and suitable for a diverse array of tasks. The foundational structure of an Artificial Neural Network (ANN), as illustrated in Figure 1, is composed of three primary types of layers: the input layer, hidden layers, and the output layer. Each layer incorporates nodes, and connections between these nodes are assigned weights. Throughout the training process, these weights are iteratively adjusted to minimize the disparity between the predicted and actual output. The Input Layer receives the initial input data, while the Hidden Layers serve as intermediate layers between the input and output layers, where the network learns complex representations. The Output Layer produces the final prediction or classification. Nodes in the neural network are linked to activation functions, introducing non-linearities to the model. Common activation functions include the sigmoid, tanh, and rectified linear unit (ReLU). These non-linearities empower the network to comprehend and represent intricate relationships within the data. Training an ANN involves exposing it to labeled data and adjusting weights through a process known as backpropagation. Backpropagation computes the gradients of the error concerning the weights, enabling the model to update its parameters in a manner that minimizes the error. This iterative process continues until the model converges to a state where predictions are sufficiently accurate.

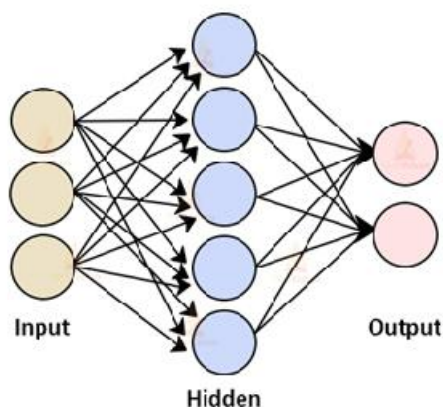


Figure 1: Architecture of ANN

Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) constitute a specialized category of artificial neural networks meticulously crafted for the processing of grid-like data, with a primary emphasis on image and spatial information. These networks have markedly transformed tasks in computer vision, playing a pivotal role in achieving cutting-edge results across various image-related applications. The distinctive architecture of CNNs encompasses convolutional layers, pooling layers, and fully connected layers. Convolutional Layers employ filters to scrutinize local regions of the input data, extracting hierarchical features such as edges, textures, and patterns. Convolutional operations entail the multiplication of filter weights with input data on an element-wise basis, followed by summation and the application of non-linear activation functions. Subsequently, pooling layers downsample the spatial dimensions of the data, thereby reducing computational complexity and emphasizing the most significant features. Common techniques in CNNs comprise max pooling and average pooling. Following the convolutional and pooling layers, fully connected layers gather the extracted features to produce the final output, akin to the architectures of conventional artificial neural networks. A noteworthy innovation in CNNs is parameter sharing, where the same set of weights (filter) is applied to multiple spatial locations in convolutional layers. This efficient practice enables CNNs to adeptly learn spatial hierarchies and patterns, imparting robustness to variations in position and scale. CNN applications span a range of domains, including Image Classification, Object Detection, Image Segmentation, Facial Recognition, and Medical Imaging. The architectural depiction of CNNs is illustrated in Figure 2.

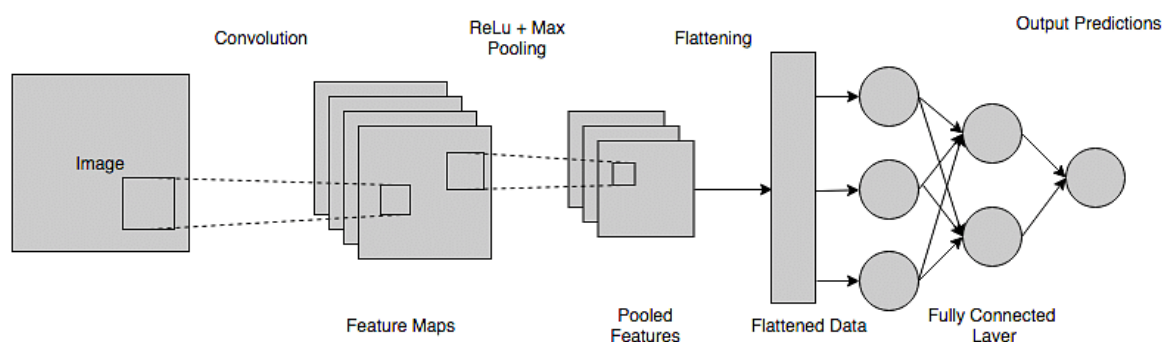


Figure 2: Architecture of CNN

Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNNs) constitute a category of artificial neural networks meticulously tailored for managing sequential data and capturing temporal dependencies. Diverging from conventional feedforward neural networks, RNNs boast connections that form directed cycles, enabling them to maintain a hidden state that preserves information from preceding time steps. This unique architecture positions RNNs as particularly adept for tasks involving sequences, such as natural language processing, speech recognition, and time-series prediction. The core architecture of an RNN features recurrent connections, facilitating the passage of information from one time step to the next. Each node within the network possesses an associated hidden state, functioning as a form of memory. At every time step, the

network takes input, updates its hidden state, and generates an output. The hidden state at any given time step encapsulates the network's memory, amalgamating information from the current input and the preceding hidden state. This mechanism enables the network to preserve context and capture temporal dependencies crucial for sequential data. The pivotal characteristic of RNNs lies in their recurrent connections, allowing the seamless transfer of information across different time steps. This recurrent nature empowers RNNs to glean insights from sequential patterns and contextual information. However, traditional RNNs grapple with challenges during training, particularly the vanishing and exploding gradient problems. These problems arise when gradients either diminish significantly (vanishing) or surge uncontrollably (exploding) during backpropagation through time, impeding the network's ability to capture long-term dependencies. To surmount the limitations of traditional RNNs, advanced architectures like Long Short-Term Memory (LSTM) have been introduced. LSTMs feature a more intricate design with specialized memory cells and gating mechanisms, effectively mitigating the vanishing gradient problem and enabling the network to grasp and remember long-term dependencies. Another variant, the Gated Recurrent Unit (GRU), shares similarities with LSTMs and employs gating mechanisms to regulate information flow, striking a balance between complexity and performance. The architectural depiction of RNNs is presented in Figure 3.

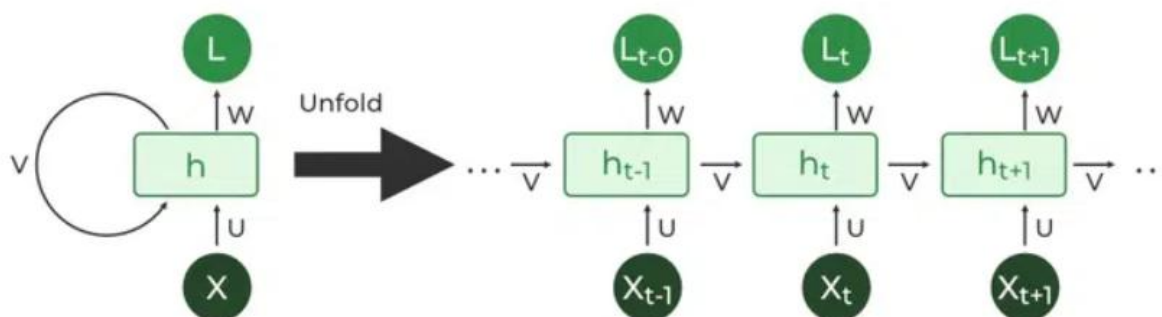


Figure 3: Architecture of RNN

4. Comparative Analysis

The characteristics comparison of Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) in terms of data type, architecture, task specialization, spatial understanding, parameter sharing, use cases, challenges, training data size, transfer learning, applications, strengths, weaknesses and examples are given in table 1.

Table 1: Comparison of ANN, CNN and RNN

Feature	Artificial Neural Networks (ANNs)	Convolutional Neural Networks (CNNs)	Recurrent Neural Networks (RNNs)
Data Type	General-purpose, suitable for diverse data types	Mainly used for structured data arranged in a grid format, such as images.	Ideal for sequential and time-series data
Architecture	Feedforward, with interconnected layers	Hierarchical, with convolutional layers and pooling	Recurrent, with feedback connections for sequential learning
Task Specialization	Versatile; applicable to various tasks	Specialized in image-related tasks such as object recognition	Specialized in sequential data tasks like natural language processing
Spatial Understanding	Limited spatial understanding	Excellent spatial understanding	Focuses on capturing temporal dependencies
Parameter Sharing	Parameters are not shared	Shared weights and local receptive fields	Shared weights and connections across time

	between features	in convolutional layers	steps
Use Cases	Generic data tasks, pattern recognition	Image classification, object detection, segmentation	NLP (Natural language processing), time-series analysis
Challenges	May struggle with complex spatial relationships	Limited effectiveness on non-grid data	Vanishing/exploding gradient problems for long-term dependencies
Training Data Size	Generally requires less data for training	Often requires large datasets for effective training	Sensitive to the amount of sequential data
Transfer Learning	Less common due to diverse applications	Common, leveraging pre-trained models for new tasks	Can benefit from pre-training on similar sequential tasks
Applications	Pattern recognition, regression	Image classification, object detection	NLP(Natural language processing), time series analysis
Strengths	Versatility, generalization to new data	Local feature learning, translation invariance	Temporal dependencies, sequential patterns
Weaknesses	Limited in handling sequential data, may require feature engineering	Limited understanding of global context, sensitive to variations	Training can be computationally expensive, vanishing/exploding gradient problem
Examples	Classic neural networks, MLPs	LeNet, AlexNet, ResNet	Vanilla RNNs, LSTM, GRU

5. CONCLUSION

In conclusion, the comparison of ANN(Artificial Neural Networks), CNN(Convolutional Neural Networks), and RNN (Recurrent Neural Networks) highlights their unique strengths and applications. ANNs excel in general-purpose tasks and pattern recognition; CNNs are highly effective in image and spatial data analysis, while RNNs demonstrate superior performance in sequential data and time-series analysis. The decision among these architectures should be influenced by the precise nature of the problem at hand, taking into account factors such as data structure, complexity, and the inherent temporal or spatial dependencies involved in the task. Ultimately, the selection between ANN, CNN, or RNN hinges on the particular requirements and characteristics of the machine learning or deep learning application in question. As research in deep learning progresses, the increasing probability of hybrid architectures and advanced variants emerging will continue to expand the frontiers of artificial intelligence.

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