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From Neurons to Convolutions: Understanding ANN and CNN

Dr Bimal Kumar Kalita

Assistant Professor(Selection), Department of Computer Applications(CDOE), Assam Don Bosco University, Sonapur, Guwahati, Assam

Abstract

Two well-known deep learning architectures are Artificial Neural Networks (ANNs) & Convolutional Neural Networks (CNNs). ANNs provide the fundamental framework for modeling complex relationships in data. On the other hand, CNNs are specialized networks designed to handle spatially structured data, like images and videos. By examining these two methods' architectures, underlying theories, uses, advantages, and disadvantages, this chapter provides a comparative analysis. Allthough both of them shares biological inspiration, the two architectures' design objectives and intended uses are very different. This chapter emphasizes on to draw a clear picture for the learners about ANN & CNN,

1. Introduction: The way that machines process information has been completely transformed by artificial intelligence and machine learning in recent time. Neural networks are one of the most important contributors among the different methods. In their most basic form, ANNs are made to simulate non-linear input-output mappings. However, CNNs, which expand ANNs by adding convolutional layers that preserve spatial information, were developed as a result of the quick expansion of computer vision and multimedia applications (LeCun, Bengio, & Hinton, 2015). This discussion explores the similarities and differences between ANNs and CNNs, emphasizing their respective strengths, weaknesses, and application areas.

2. History:

2.1 History of Artificial Neural Networks (ANNs)

a. 1940s–1950s:

In 1943, The McCulloch & Pitts Model came into effect. Warren McCulloch and Walter Pitts put forth a basic model of artificial neurons using binary thresholds, This is considered as Neural network's first mathematical model.

In 1949, Hebbian Learning came to light. Donald Hebb postulated that when neurons fire in unison, synaptic strength rises. That is "Neurons that fire together wire together."

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b. In 1958 the concept of Perceptron arrived and a huge leap in this advancement happened. Perceptron is a single-layer neural network, which were created by Frank Rosenblatt. It was capable of learning linearly separable functions & is regarded as technological breakthrough in the field of AI.

c. Around 1969, Minsky and Papert published a book titled "*Perceptrons*," that outlined the drawbacks of single-layer perceptrons. One such example is their incapacity to solve XOR. This resulted in the first AI Winter, a drop in neural network research.

d. Revival of ANN took place after Rumelhart, Hinton, & Williams made backpropagation widely used in 1986. Backpropagation technique made it possible for multi-layer neural networks (MLPs) to learn. This signaled the revival of ANN research & subsequently led to time series prediction, speech recognition, and OCR applications..

e. During 1990s, with tremendous growth and associated difficulties expanding, applications and theoretical work still had trouble training deep networks. This was primarily because of limited processing power and vanishing gradients.

f. The Deep Learning Era Begins in 2006. Deep Belief Networks (DBNs) were first presented by Geoffrey Hinton, who also demonstrated how layer-wise unsupervised pre-training could aid in the convergence of deep networks. And the deep learning movement began as a result.

2.2 History of Convolutional Neural Networks (CNNs)

1. In 1980, inspired by the visual cortex, Kunihiko Fukushima proposed the Neocognitron. He presented the ideas of subsampling and convolution.

2. In the year 1989, the first CNN, LeNet-5, was created by Yann LeCun to recognize handwritten digits, such as ZIP codes. It introduced convolutional, pooling, fully connected, and backpropagation-trained layers.

3. During 1990s–2000s, CNNs remained in the Shadows because CNNs needed a lot of computation. Training deep CNNs was difficult because of limited GPUs and non availability of large datasets as small datasets were only in hand. They were mostly used for specialized image processing tasks.

4. In 2012, AlexNet brought the breakthrough. Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton developed AlexNet, which won ImageNet 2012 by a large margin compared to other models. Important advances included by them were GPU acceleration, Dropout for regularization, ReLU activation, and deep architecture.

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5. From 2014 till now, CNN architectures have progressed rapidly. Examples include VGGNet (2014), GoogLeNet/Inception (2014), ResNet (2015), which introduced residual connections, DenseNet, EfficientNet, and Vision Transformers (ViTs), which are hybrid and post-CNN models came to existence and forward stride is still on.

CNN Applications: CNNs are used in image and video recognition, object detection, medical imaging, autonomous driving, and natural language processing, such as text classification etc..

Summary table

Era	ANN Milestone	CNN Milestone
1940s–50s	McCulloch-Pitts model, Hebbian learning	—
1958	Perceptron (Rosenblatt)	—
1969	Perceptron limitations (Minsky & Papert)	—
1980	Backpropagation revival	Neocognitron (Fukushima)
1989	MLPs with backpropagation	LeNet-5 (LeCun)
2006+	Deep learning with DBNs (Hinton)	—
2012+	Resurgence with GPU-trained deep ANNs	AlexNet, ResNet, EfficientNet, MobileNet etc.

3. Architecture

3.1 Artificial Neural Network (ANN): ANNs consist of an input layer, one or more hidden layers, and an output layer. Each neuron in a given layer is connected to all neurons in the next layer, forming a fully connected architecture (Goodfellow, Bengio, & Courville, 2016).

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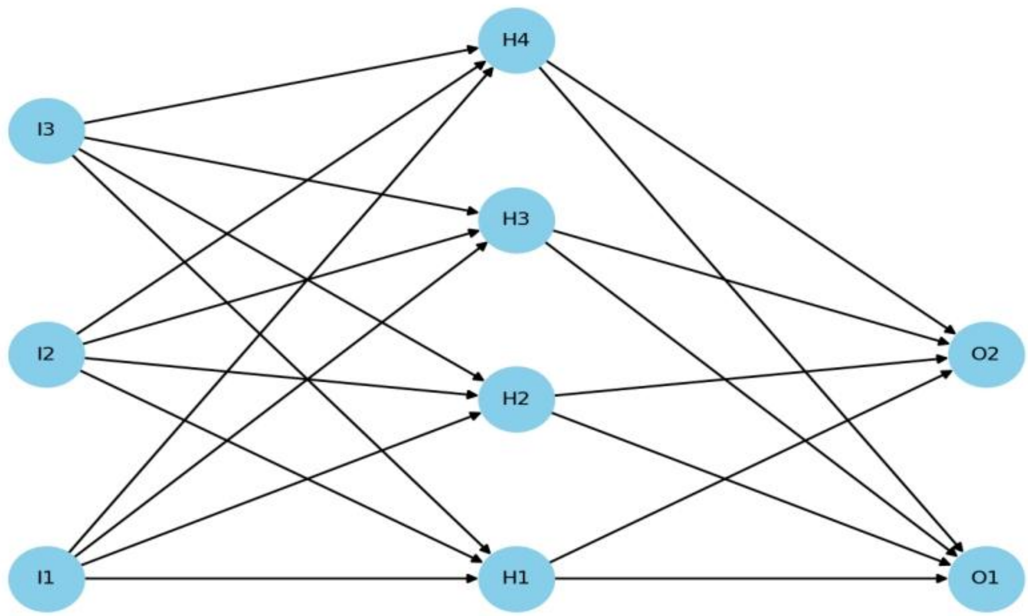
Figure 1. Basic Architecture of an Artificial Neural Network (ANN)



Such networks are very flexible and can represent complex non-linear functions. However, when applied to high-dimensional data like images, they require too many parameters, which can lead to inefficiency.

3.2 Convolutional Neural Network (CNN): CNNs include convolutional and pooling layers along with fully connected layers. Convolutional filters let CNNs capture local patterns such as edges, textures, and shapes (Krizhevsky, Sutskever, & Hinton, 2012).

Pooling layers reduce dimensionality and improve computational efficiency while maintaining essential information. The hierarchical learning mechanism enables CNNs to create more complex feature representations. That makes them ideal for analyzing images and videos.

4. Working Principles

4.1 ANN Operation: The input features appear as a flattened vector. Each neuron computes a weighted sum of inputs and then applies an activation function. The absence of built-in spatial awareness limits ANNs in tasks that involve structured data like images (Schmidhuber, 2015).

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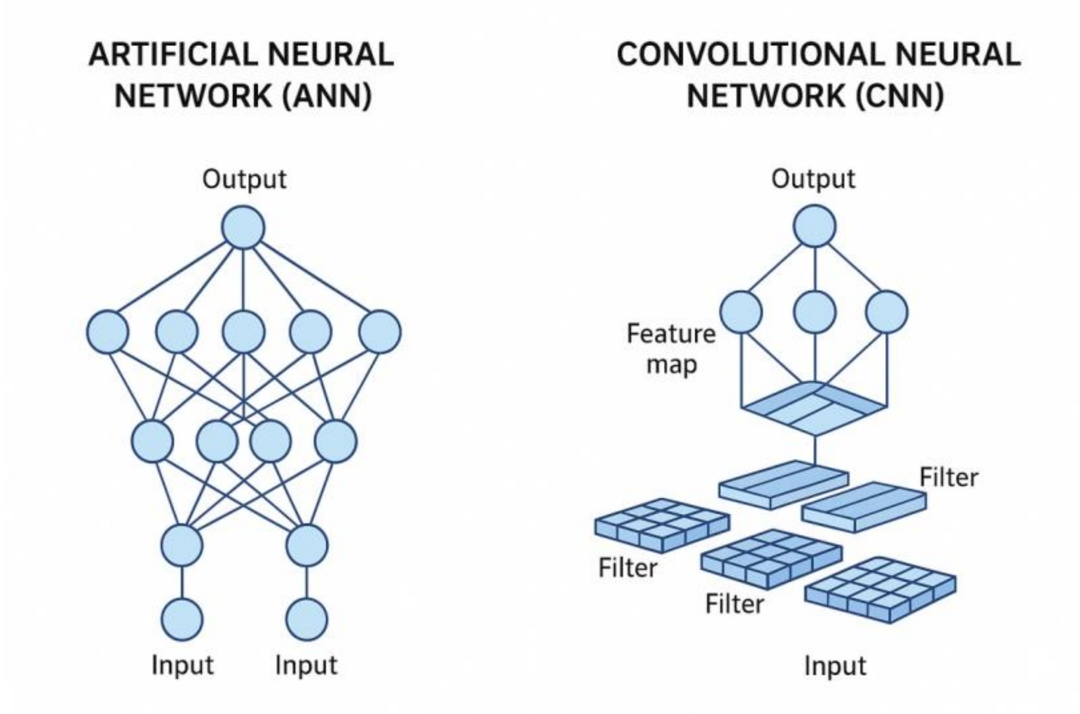
4.2 CNN Operation: CNNs process inputs with convolutional filters that preserve spatial relationships among pixels. Pooling layers cut down features to reduce redundancy. The final fully connected layers handle classification or regression tasks. This setup enables CNNs to learn features automatically rather than depending on manually created feature extraction.



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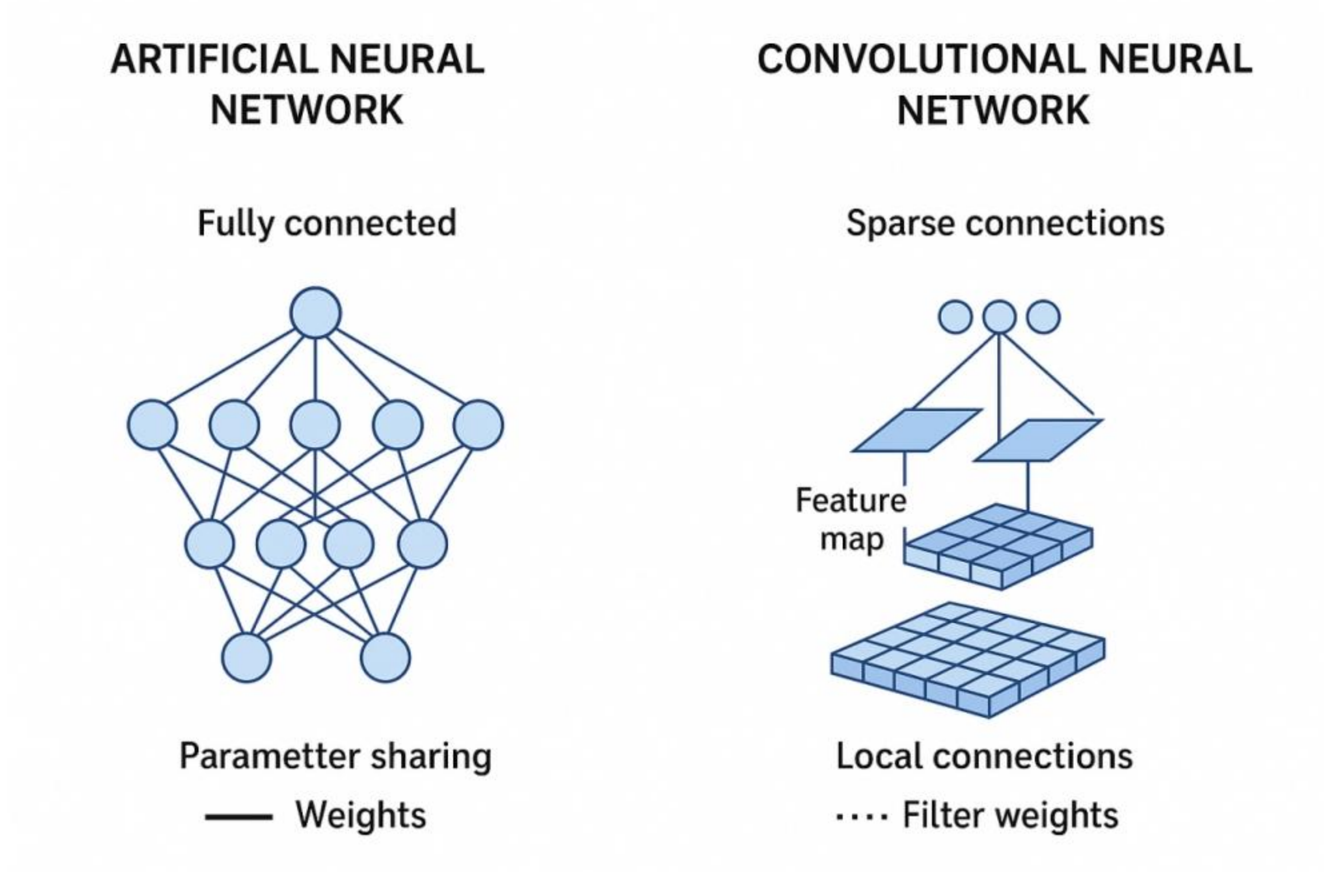

5. Key Differences

Aspect	Neural Network (ANN)	Convolutional Neural Network (CNN)
Data Handling	Treats input as flat vectors	Preserves spatial/temporal structure
Connections	Fully connected	Local connectivity, shared weights
Parameters	Very high for large inputs	Reduced due to weight sharing
Applications	Tabular data, simple prediction	Image, video, speech, NLP
Efficiency	Less efficient for image data	Highly efficient for spatial data

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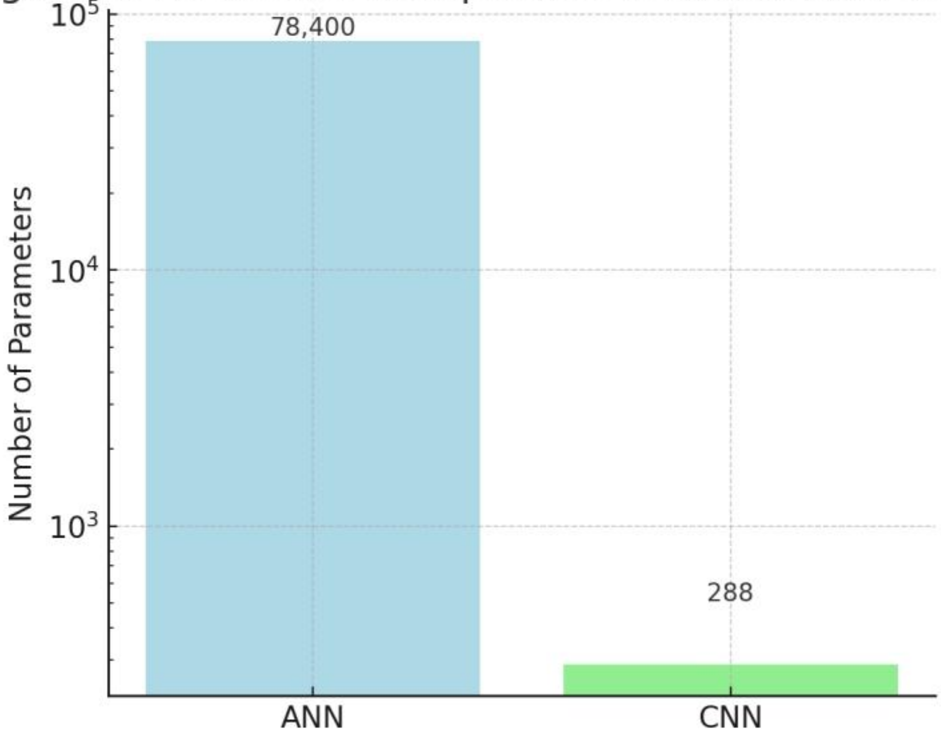
Figure 3. Parameter Comparison between ANN and CNN



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6. Applications

6.1 ANN Applications: ANNs are often used in predictive analytics, financial forecasting, customer churn prediction, and healthcare diagnostics. These applications depend on structured tabular datasets (Haykin, 2009).

6.2 CNN Applications: CNNs are the top choice for computer vision tasks such as image recognition, object detection, medical imaging, and autonomous driving. Their ability to learn spatial hierarchies makes them crucial for large-scale vision applications (Rawat & Wang, 2017).

7. Advantages and Limitations

7.1 ANN:

Advantages: It is general-purpose, easy to implement, and effective for small to medium-sized datasets.

Limitations: It has poor scalability for high-dimensional data, lacks built-in spatial feature extraction, and carries a risk of overfitting.

7.2 CNN:

Advantages: Automatic feature extraction, reduced parameter count, and robustness to distortions.

Limitations: Requires large labeled datasets, is computationally expensive, and needs complex hyperparameter tuning.

8. Conclusion

ANNs and CNNs, while inspired by biology, serve different purposes in deep learning. ANNs work best with structured, non-spatial data. In contrast, CNNs are great for spatially correlated data, like images and videos. Their complementary roles often lead to hybrid models. In these models, CNNs extract features and ANNs, specifically the fully connected layers, handle the final classification. The decision to use one over the other relies on the data characteristics and the specific problem at hand.

References:

[1] Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

[2] Haykin, S. (2009). *Neural networks and learning machines* (3rd ed.). Pearson.

[3] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. *Communications of the ACM, 60*(6), 84–90. https://doi.org/10.1145/3065386

[4] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444. https://doi.org/10.1038/nature14539

[5] Rawat, W., & Wang, Z. (2017). Deep convolutional neural networks for image classification: A comprehensive review. *Neural Computation*, *29*(9), 2352–2449. https://doi.org/10.1162/neco_a_00990

[6] Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural Networks, 61*, 85–117. https://doi.org/10.1016/j.neunet.2014.09.003