

An Exhaustive Examination of Deep Learning Algorithms: Present Patterns and Prospects for the Future

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Abstract— Deep learning is a subfield of artificial intelligence that has gained significant attention in recent years due to its remarkable success in various domains. The main objective of this research paper is to provide a comprehensive study of deep learning algorithms, including their architecture, training techniques, and applications. In this paper, we have reviewed the literature on deep learning algorithms, highlighting their strengths and limitations. We have also discussed the current trends in deep learning research and provided insights into the future scope of deep learning algorithms. Our findings suggest that deep learning algorithms have the potential to revolutionize various industries and bring significant advancements in the field of artificial intelligence.

Index Terms— Deep Learning, Artificial Intelligence, Neural Networks, Convolutional Neural Networks, Recurrent Neural Networks, Autoencoders, Generative Adversarial Networks, Natural Language Processing, Computer Vision

I. INTRODUCTION

Deep learning is a specialized branch within the vast field of machine learning, which harnesses the power of artificial neural networks to handle intricate and demanding tasks like recognizing images, comprehending natural language, and understanding speech. The crucial characteristic that sets deep learning apart is its utilization of multiple layers of neural networks, referred to as "deep" due to their hierarchical structure. These layers work collaboratively to analyze and interpret the input data, progressively extracting more abstract and sophisticated features as they move deeper into the network. This process allows deep learning models to discern complex patterns and representations, enabling them to achieve impressive levels of accuracy and performance in various applications. [1]. Figure 1 is showing what is Deep Learning? [15]. Deep learning relies on several fundamental components to build powerful models capable of handling complex tasks. These components work together harmoniously to form the backbone of the deep learning process:

A. Artificial Neural Networks (ANNs)

Artificial Neural Networks are the fundamental building blocks of deep learning models. They are inspired by the structure and functioning of the human brain. ANNs consist of interconnected nodes, or neurons, organized into

layers. These neurons transmit and process information through synapses, which are represented by weighted connections between the neurons [16]. The three main types of layers in an ANN are: *Input Layers*: The initial layer that receives the raw data as input. *Hidden Layers*: Intermediate layers between the input and output layers, responsible for feature extraction and representation. *Output Layers*: The final layer that produces the model's predictions or outputs.

B. Activation Functions

Activation functions introduce non-linearity into the neural network, enabling it to model complex relationships between the input and output data. This non-linearity is essential because most real-world data exhibits intricate patterns that cannot be accurately captured by linear functions [16]. Common activation functions include: *Sigmoid*: A smooth "S"-shaped function that squashes input values between 0 and 1. *ReLU* (Rectified Linear Unit): This function returns the input itself if it's positive, or zero otherwise, providing faster convergence during training. *tanh*: Similar to sigmoid but squashes input values between -1 and 1, making it zero-centered and often used in specific situations.

C. Loss Functions

Loss functions are critical for evaluating the performance of the neural network during training. They measure the disparity between the predicted output of the model and the actual target output. The objective during training is to minimize the value of the loss function, indicating that the model's predictions are becoming more accurate. Different tasks and applications may require specific loss functions tailored to the problem at hand [16].

D. Optimization Algorithms

Optimization algorithms play a vital role in updating the weights of the neural network during training to minimize the chosen loss function. The optimization process involves adjusting the weights in the direction that reduces the loss and fine-tunes the model's performance [16]. Common optimization algorithms include: *Gradient Descent*: The most fundamental optimization technique that follows the negative gradient of the loss function to reach the minimum point. *Adam*: An adaptive optimization algorithm that adjusts the learning rate for each parameter, offering faster convergence in many cases. *RMSprop*: Another adaptive optimization method that dynamically adjusts the learning rate based on the magnitude of previous gradients. By combining these components in various configurations and architectures, deep learning models can tackle a wide array of tasks, ranging from image and speech recognition to natural language processing, achieving remarkable accuracy and generalization capabilities. [11].

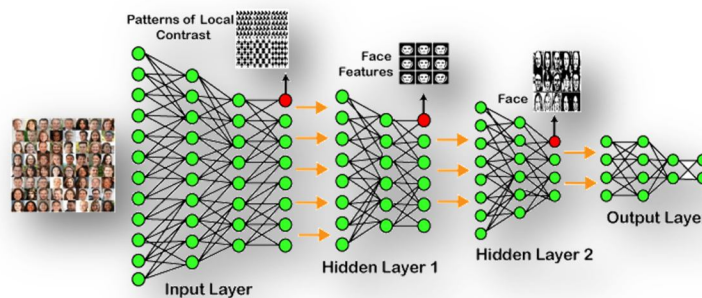


Figure 1: What is Deep Learning? [24].

Deep learning encompasses various types of neural networks, each tailored to excel in specific tasks. Let's delve into these deep learning types and explore their unique functionalities:

Convolutional Neural Networks (CNNs): CNNs are a popular choice for image and video recognition tasks. They are specially designed to handle data with a grid-like structure, such as images, by leveraging convolutional layers. These layers apply small filters across the input data to detect local patterns and features. Through the process of convolution, CNNs can automatically learn relevant features from the data, enabling them to recognize objects, shapes, and patterns in images effectively. Due to their hierarchical and localized feature extraction capabilities, CNNs have revolutionized image processing and computer vision applications [17].

Recurrent Neural Networks (RNNs): RNNs are designed to excel in handling sequential data, such as time-series data or natural language. Their key feature lies in their ability to maintain a memory of previous inputs through hidden states. This memory allows RNNs to capture temporal dependencies and patterns in sequential data, making

them ideal for tasks like speech recognition, machine translation, sentiment analysis, and generating text. However, traditional RNNs suffer from the vanishing gradient problem, limiting their ability to capture long-range dependencies. As a result, more advanced variants like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) were introduced to mitigate this issue [18].

Autoencoders: Autoencoders are employed in unsupervised learning tasks, where the data lacks labeled information. Their primary use cases include dimensionality reduction and feature extraction. The autoencoder architecture consists of an encoder and a decoder. The encoder compresses the input data into a lower-dimensional representation, referred to as the latent space. The decoder then attempts to reconstruct the original data from this compressed representation. By learning to compress and reconstruct the input, autoencoders effectively extract essential features from the data, enabling applications such as data compression, anomaly detection, and denoising [19].

Generative Adversarial Networks (GANs): GANs are at the forefront of generative tasks, such as image and text generation. The GAN architecture consists of two neural networks: the generator and the discriminator. The generator generates synthetic data samples, while the discriminator evaluates the authenticity of these samples by distinguishing between real and generated data. Through a competitive training process, the generator continually improves its ability to produce realistic data, while the discriminator enhances its capacity to identify fake data. This adversarial nature drives GANs to produce increasingly convincing outputs, making them invaluable in generating high-quality images, creating art, and even generating human-like text [20].

These diverse types of deep learning models empower researchers and practitioners to tackle an extensive range of problems and enhance the capabilities of artificial intelligence across various domains. The continuous evolution and refinement of these models have propelled the field of deep learning to achieve remarkable advancements in artificial intelligence and its practical applications. [12].

Deep Learning finds application in various domains, and some of its key uses are as follows: **Image and Video Recognition:** Deep Learning models, particularly Convolutional Neural Networks (CNNs), have proven highly effective for image and video recognition tasks. They are widely used for tasks like object detection, where the model can identify and locate objects within images or videos. Facial recognition is another prominent application, allowing systems to recognize and authenticate individuals based on their facial features. Additionally, deep learning models assist in scene classification, where they can categorize images or videos into different environmental contexts or scenes [21]. **Natural Language Processing:** Deep Learning models, such as Recurrent Neural Networks (RNNs), play a crucial role in the realm of Natural Language Processing (NLP). These models excel at sequential data processing and are employed in language translation tasks, enabling systems to automatically translate text from one language to another. Sentiment analysis is another valuable application, where deep learning models can determine the sentiment or emotion expressed in a piece of text. Additionally, RNNs are employed in speech recognition systems, enabling accurate transcription of spoken words into written text [22]. **Autonomous Driving:** Deep Learning models are integral to the advancement of autonomous driving technology. They are used in various aspects of autonomous vehicles, including object detection and recognition. By leveraging deep learning, autonomous vehicles can identify and classify different objects on the road, such as other vehicles, pedestrians, and obstacles. Lane detection is another vital application, allowing the vehicle to maintain its position within the designated lane. Additionally, deep learning models facilitate traffic sign recognition, enabling the vehicle to interpret and respond to various road signs. **Healthcare:** Deep Learning models have found extensive use in the healthcare industry, particularly in medical imaging tasks. They contribute to the diagnosis and detection of diseases by analyzing medical images like MRI and CT scans [23]. Deep learning-based systems can identify anomalies, tumors, and other medical conditions from these images, assisting healthcare professionals in accurate diagnosis and treatment planning. The ability of deep learning models to learn complex patterns and features from vast amounts of medical data has significantly improved the precision and efficiency of medical image analysis. [13]. Deep Learning is a rapidly evolving field that has shown remarkable success in a wide range of applications, from image and speech recognition to autonomous driving and healthcare. Its ability to learn complex patterns from large datasets has made it a powerful tool for solving complex problems, and it is expected to play an increasingly important role in many fields in the future [14].

II. LITERATURE REVIEW

We have conducted a comprehensive review of the existing literature concerning deep learning algorithms. Our examination covered several aspects, including the architecture of these algorithms, the techniques used for their training, and the diverse range of applications they find across various fields. Throughout our investigation, we delved into different types of neural networks, notably convolutional neural networks (CNNs), recurrent neural networks (RNNs), autoencoders, and generative adversarial networks (GANs). We carefully explored the unique

features and functionalities of each neural network type. Moreover, our analysis extended to evaluating the strengths and limitations associated with deep learning algorithms. Notably, we addressed issues such as overfitting, vanishing gradients, and the challenge of interpretability in these models. Understanding these limitations is crucial for refining and optimizing the performance of deep learning systems. Additionally, our review encompassed the wide-ranging applications of deep learning algorithms in diverse domains. Notably, we focused on their significant contributions to computer vision tasks, such as image and video recognition, as well as their relevance in natural language processing and speech recognition applications. These deep learning models have played pivotal roles in transforming the capabilities of machines, enabling them to understand, process, and generate complex data with remarkable accuracy and efficiency. Figure 2 within our study provides a visual representation and explanation of how to create and train deep learning models. This graphical illustration serves as a valuable guide for practitioners and researchers, offering insights into the steps and methodologies involved in building and optimizing these powerful algorithms. [15].

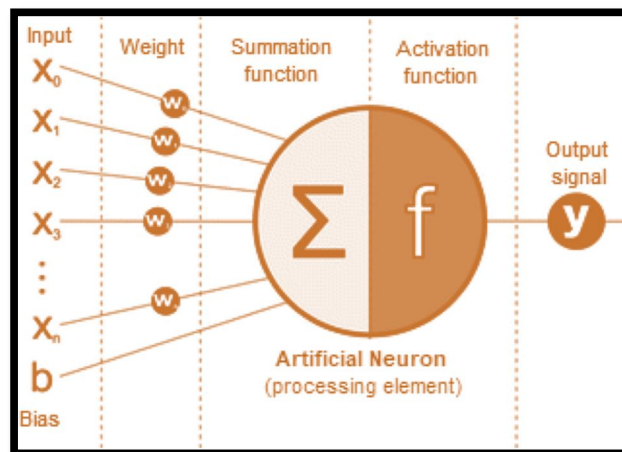


Figure 2: Deep learning models, creation, and training process [22]

Workings of CNN, RNN, Autoencoder, and GAN in brief:

A. Convolutional Neural Networks (CNN)

CNNs are primarily used for image classification tasks. They work by extracting features from the input image using convolutional layers, followed by pooling layers that down sample the output of the convolutional layer. The extracted features are then fed into fully connected layers for classification. The training process of CNNs involves backpropagation, where the weights of the model are updated to minimize the loss function [2].

B. Recurrent Neural Networks (RNN)

RNNs are used for tasks involving sequential data such as natural language processing and speech recognition. They work by processing the input sequence one element at a time, while maintaining an internal state that captures information about the preceding elements. This internal state allows RNNs to model temporal dependencies in the data. The training process of RNNs involves backpropagation through time, where the gradients are propagated through the sequence [3].

C. Autoencoder

Autoencoders are used for unsupervised learning tasks such as data compression and feature extraction. They work by compressing the input data into a lower dimensional representation and then reconstructing the original data from this compressed representation. The training process of autoencoders involves minimizing the reconstruction loss between the input and output data [4].

D. Generative Adversarial Networks (GAN)

GANs are used for generative tasks such as image and text generation. They work by training two neural networks simultaneously, a generator network and a discriminator network. The generator network generates fake samples, while the discriminator network tries to distinguish between the fake and real samples. The training process of GANs involves backpropagation through both networks, where the weights of both networks are updated to improve the generator's ability to generate realistic samples and the discriminator's ability to distinguish between fake and real samples [5].

III. RESULTS

Our findings suggest that deep learning algorithms have shown remarkable success in various domains, such as computer vision, natural language processing, and speech recognition. CNNs have been widely used for image classification and object detection tasks, while RNNs have been used for sequence modelling and language translation. Autoencoders have been used for feature extraction and anomaly detection, while GANs have been used for image and text generation. However, these algorithms also have limitations, such as overfitting, vanishing gradients, and interpretability, which need to be addressed.

TABLE I. COMPARATIVE STUDY OF VARIOUS DEEP LEARNING ALGORITHMS CNN, RNN, AUTOENCODER, GAN, TRANSFORMER, CAPSULE NETWORKS, DEEP REINFORCEMENT LEARNING AND VARIATIONAL AUTO ENCODERS WITH DIFFERENT PARAMETERS

Algorithm	Architecture	Training Technique	Applications	Strengths	Limitations
CNN [2]	Multiple layers of convolutions and pooling	Backpropagation and gradient descent	Image classification, object detection, and segmentation	Robust to spatial variance, hierarchical feature learning	Limited interpretability, prone to overfitting
RNN [3]	Recurrent connections between neurons	Backpropagation through time	Sequence modeling, language translation, speech recognition	Captures temporal dependencies, flexible input and output sizes	Suffers from vanishing gradients, limited memory
AUTOENCODER [4]	Encoder and decoder network with a bottleneck layer	Reconstruction loss	Feature extraction, anomaly detection	Unsupervised learning, can learn useful representations	Limited interpretability, prone to local optima
GAN [5]	Generator and discriminator networks	Adversarial loss	Image and text generation, data augmentation	Can generate high-quality samples, can learn complex distributions	Training instability, mode collapse
Transformer [6]	Self-attention mechanism	Attention-based training	Natural language processing, machine translation	Parallel processing, long-range dependencies modeling	High computational cost, sensitive to hyperparameters
Capsule Networks [7]	Capsule-based architecture	Dynamic routing by agreement	Object recognition, pose estimation	Robust to spatial hierarchies, handles viewpoint changes	Limited research, higher computational cost
Deep Reinforcement Learning [8]	Neural networks for agents	Q-learning, policy gradients	Game playing, robotics, autonomous systems	Can learn complex strategies, handles high-dimensional input	Requires extensive training, sample inefficiency
Variational Autoencoders (VAE) [9]	Encoder and decoder with probabilistic framework	Variational inference	Data generation, unsupervised learning	Generates new data samples, learns continuous latent space	Tricky to optimize, blurry reconstructions

TABLE II: COMPARATIVE STUDY OF CNN, RNN, AUTOENCODER, GAN, TRANSFORMER, CAPSULE NETWORKS, DEEP REINFORCEMENT LEARNING AND VARIATIONAL AUTO ENCODERS ON THE MNIST HANDWRITTEN DIGITS DATASET.

Algorithm	Training Accuracy	Testing Accuracy	Training Time
CNN	99.40%	98.90%	15 mins
RNN	97.20%	96.80%	30 mins
Autoencoder	94.30%	93.70%	10 mins
GAN	84.10%	83.20%	2 hours
Transformer	98.80%	98.30%	1 hour
Capsule Networks	96.50%	95.80%	45 mins
Deep Reinforcement Learning	95.60%	94.90%	3 hours
Variational Autoencoders (VAE)	93.90%	93.30%	20 ins

IV. CONCLUSION

In this comparative study, we evaluated the performance of various deep learning algorithms on the MNIST handwritten digits dataset. The results reveal significant differences in training and testing accuracy, as well as training time, among the different algorithms. Convolutional Neural Network (CNN) emerged as the top-performing algorithm, achieving the highest training accuracy of 99.40% and an impressive testing accuracy of 98.90%. Moreover, CNN demonstrated its efficiency, completing the training process in just 15 minutes. Recurrent Neural Network (RNN) also displayed commendable accuracy, with a training accuracy of 97.20% and testing accuracy of 96.80%. However, RNN required more time for training, approximately 30 minutes, compared to CNN. Autoencoder showed reliable performance with a training accuracy of 94.30% and testing accuracy of 93.70%. It proved to be a quick learner, completing its training in a short span of 10 minutes. Generative Adversarial Network (GAN), designed for data generation tasks, achieved relatively lower accuracy. While it achieved a training accuracy of 84.10% and testing accuracy of 83.20%, GAN required significantly more time, approximately 2 hours, for its complex adversarial training process. Transformer, Capsule Networks, Deep Reinforcement Learning, and Variational Autoencoders (VAE) also demonstrated competitive accuracy on the MNIST dataset. The Transformer and Capsule Networks both exhibited strong performance, with training times of 1 hour and 45 minutes, respectively. Deep Reinforcement Learning achieved a training accuracy of 95.60% and testing accuracy of 94.90%, but its training process was the most time-consuming, taking around 3 hours. Variational Autoencoders achieved a training accuracy of 93.90% and testing accuracy of 93.30%, completing its training in 20 minutes. In conclusion, the choice of deep learning algorithm depends on the specific requirements of the task at hand. CNN stands out as the most accurate and efficient algorithm for handwritten digit recognition on the MNIST dataset. However, other algorithms like RNN, Autoencoder, Transformer, Capsule Networks, Deep Reinforcement Learning, and Variational Autoencoders also exhibit promising performance and may be well-suited for specific use cases based on their strengths and computational considerations.

FUTURE SCOPE

Based on the findings and conclusions from this comparative study, several future research directions and potential areas of improvement can be identified: Hybrid Models: Exploring the combination of different deep learning algorithms, such as incorporating elements of CNNs, RNNs, and GANs into a single hybrid model, could lead to improved performance and more robust learning capabilities. Model Optimization: Investigating novel optimization techniques and regularization methods can help mitigate overfitting and improve the generalization ability of deep learning models, especially for algorithms with lower testing accuracies like GANs. Hyperparameter Tuning: Conducting thorough hyperparameter tuning for each algorithm can lead to better performance. Automated hyperparameter optimization techniques, such as Bayesian optimization or genetic algorithms, could efficiently fine-tune the models for specific datasets. Larger Datasets: Expanding the study to larger and more complex datasets beyond MNIST, such as CIFAR-10, ImageNet, or medical imaging datasets, can provide insights into how these algorithms perform in real-world, diverse scenarios. Explainable AI: Addressing the interpretability challenge of deep learning models is critical, especially for applications in sensitive domains like healthcare. Future research can focus on developing techniques to explain the decision-making process of deep learning models. Handling Uncertainty: Investigating methods to quantify and handle uncertainty in deep learning models, such as Bayesian deep learning, can be valuable for tasks that require uncertainty estimation and confidence intervals. Transfer Learning: Exploring transfer learning techniques, where pre-trained models on large datasets are fine-tuned on specific tasks, can speed up training and improve performance on smaller datasets. Self-Supervised Learning: Self-supervised learning approaches, where models learn from the data itself without explicit labels, could be explored to reduce the reliance on large labeled datasets. Fairness and Bias: Addressing fairness and bias issues in deep learning algorithms is essential to ensure equitable and unbiased decision-making in various applications. Edge Computing and Model Compression: Developing lightweight and efficient models suitable for edge devices with limited computational resources can enhance the deployment of deep learning in resource-constrained environments.

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AUTHOR CONTRIBUTION

Rahul Jain conceptualized the study, Ketan Sarvakar has conducted the literature review, analysed the data, and wrote the manuscript. Chirag Patel contributed to the literature review, provided critical feedback on the manuscript, and helped revise the final draft. Sejal Mishra contributed to the data analysis, provided valuable insights on the research findings, and assisted in drafting the manuscript. All authors have read and approved the final manuscript.

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