

A Review of Deep Learning Techniques: Basic Algorithms and Use Cases

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Abstract— Deep Learning (DL), a specialized branch of artificial intelligence (AI) and machine learning (ML), has revolutionized modern computing by enabling systems to learn hierarchical representations from large volumes of data. Unlike conventional machine learning algorithms that require manual feature engineering, deep learning models automatically extract meaningful features through multiple hidden layers of artificial neural networks. Recent advances in computational power, graphics processing units (GPUs), cloud computing, and the availability of large-scale datasets have accelerated the adoption of deep learning across diverse application domains. This review paper provides a comprehensive overview of fundamental deep learning concepts, basic algorithms, and their real-world applications. The paper discusses the architecture, working principles, strengths, limitations, and practical implementations of major deep learning algorithms, including Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Autoencoders, Generative Adversarial Networks (GANs), and Transformer-based models. Furthermore, various use cases in healthcare, agriculture, finance, cybersecurity, transportation, natural language processing, robotics, and smart cities are explored. The paper also highlights current research challenges such as data scarcity, computational complexity, explainability, bias, privacy, and ethical concerns. Finally, future research directions involving Explainable AI, Federated Learning, Edge AI, TinyML, Graph Neural Networks, multimodal learning, and Generative AI are discussed. This review serves as a valuable reference for researchers, academicians, and practitioners interested in understanding the current state and future prospects of deep learning technologies.

Index Terms— Deep Learning, Artificial Intelligence, Neural Networks, CNN, RNN, LSTM, Transformers, Computer Vision, Natural Language Processing, Machine Learning.

I. INTRODUCTION

Artificial Intelligence (AI) has become one of the most influential technologies of the twenty-first century. AI enables computer systems to perform tasks that traditionally require human intelligence, including reasoning, learning, decision-making, language understanding, image recognition, and problem-solving. Among the numerous branches of AI, Machine Learning (ML) has emerged as one of the most successful approaches for developing intelligent systems capable of learning from historical data without explicit programming.

Deep Learning (DL) represents an advanced subset of machine learning that utilizes artificial neural networks with multiple hidden layers to automatically learn hierarchical feature representations. Unlike traditional machine learning algorithms that depend heavily on handcrafted features, deep learning models learn directly from raw data through nonlinear transformations. This capability has significantly improved performance in complex tasks such as image classification, speech recognition, object detection, language translation, medical diagnosis, autonomous driving, and recommendation systems.

The remarkable success of deep learning can be attributed to several technological advancements. The availability of massive datasets, improvements in Graphics Processing Units (GPUs), cloud computing infrastructure, distributed learning frameworks, and optimized deep learning libraries such as TensorFlow, PyTorch, and Keras have enabled researchers to train increasingly complex neural network architectures. Furthermore, modern optimization algorithms, activation functions, and regularization techniques have improved convergence speed and reduced overfitting, making deep learning more practical for real-world applications.

Today, deep learning plays a critical role across numerous industries. In healthcare, deep learning assists physicians in detecting diseases from medical images, predicting patient outcomes, and developing personalized treatment plans. In agriculture, intelligent systems diagnose crop diseases, estimate yield, monitor plant health, and optimize irrigation using drone imagery and satellite data. Financial institutions utilize deep learning for fraud detection, credit scoring, stock market prediction, and risk assessment. Similarly, autonomous vehicles employ deep neural networks for object detection, lane recognition, traffic sign identification, and decision-making under dynamic environments.

Although deep learning has achieved remarkable success, several challenges remain unresolved. Large computational requirements, extensive labeled datasets, limited interpretability, security vulnerabilities, privacy concerns, algorithmic bias, and high energy consumption continue to limit widespread deployment in resource-constrained environments. Consequently, researchers are actively exploring Explainable AI (XAI), Federated Learning, Edge AI, TinyML, Green AI, and trustworthy artificial intelligence to overcome these limitations.

This review paper presents a comprehensive overview of deep learning fundamentals, major algorithms, application domains, challenges, and emerging research directions. The objective is to provide readers with a structured understanding of the evolution and future scope of deep learning technologies.

II. BASIC DEEP LEARNING TECHNIQUES

Deep learning techniques are a specialized subset of machine learning that utilize artificial neural networks with multiple hidden layers to automatically learn hierarchical feature representations from large-scale datasets. Unlike traditional machine learning methods, deep learning algorithms minimize the need for manual feature engineering by extracting relevant features directly from raw data. Based on the learning strategy and the availability of labeled data, deep learning techniques are generally classified into three major categories: supervised deep learning, unsupervised deep learning, and reinforcement learning. Each technique employs different training mechanisms and is suitable for specific types of real-world applications.

2.1 Supervised Deep Learning

Supervised deep learning is the most widely used learning paradigm, where deep neural networks are trained using labeled datasets containing both input data and corresponding target outputs. During training, the model learns the relationship between input features and the desired output by minimizing a predefined loss function through backpropagation and optimization algorithms such as Stochastic Gradient Descent (SGD) or Adam. Once trained, the model can accurately classify unseen data or predict future outcomes.

Supervised deep learning has demonstrated outstanding performance in image classification, object detection, speech recognition, medical diagnosis, natural language processing, sentiment analysis, and recommendation systems. supervised deep learning algorithms include:

1. Artificial Neural Networks (ANN)
2. Convolutional Neural Networks (CNN)
3. Recurrent Neural Networks (RNN)
4. Long Short-Term Memory Networks (LSTM)
5. Gated Recurrent Units (GRU)
6. Vision Transformers (ViT)

2.2 Unsupervised Deep Learning

Unsupervised deep learning utilizes unlabeled datasets, where no predefined target labels are available. The objective of these algorithms is to automatically discover hidden structures, meaningful representations, clusters, or latent features from the input data without human supervision. These techniques are particularly useful for dimensionality reduction, anomaly detection, feature extraction, image generation, and data compression.

Unsupervised deep learning models learn compact feature representations that can subsequently improve the performance of supervised learning algorithms. unsupervised deep learning algorithms include:

1. Autoencoders (AE)
2. Variational Autoencoders (VAE)
3. Generative Adversarial Networks (GAN)
4. Restricted Boltzmann Machines (RBM)
5. Deep Belief Networks (DBN)
6. Self-Organizing Maps (SOM)

2.3 Reinforcement Learning

Reinforcement Learning (RL) is a learning paradigm in which an intelligent agent learns to make optimal

decisions by interacting with a dynamic environment. Instead of learning from labeled examples, the agent continuously observes the current state, performs an action, receives a reward or penalty, and updates its policy to maximize the cumulative reward over time. Reinforcement learning is particularly effective for sequential decision-making problems where optimal actions depend on long-term outcomes.

Recent advances in Deep Reinforcement Learning (DRL) combine deep neural networks with reinforcement learning algorithms, enabling intelligent agents to solve highly complex tasks in

robotics, autonomous driving, game playing, industrial automation, resource allocation, and smart control systems. Reinforcement learning algorithms include:

1. Q-Learning
2. Deep Q-Networks (DQN)
3. Double Deep Q-Networks (DDQN)
4. Deep Deterministic Policy Gradient (DDPG)
5. Proximal Policy Optimization (PPO)
6. Actor-Critic Methods (A2C/A3C)
7. Soft Actor-Critic (SAC)

Table 2.1 Classification of Basic Deep Learning Techniques

Learning Technique	Training Data	Objective	Representative Algorithms	Major Applications
Supervised Deep Learning	Labeled Data	Classification and Prediction	ANN, CNN, RNN, LSTM, GRU, ViT	Image Classification, Medical Diagnosis, NLP, Speech Recognition
Unsupervised Deep Learning	Unlabeled Data	Feature Learning and Pattern Discovery	Autoencoder, VAE, GAN, RBM, DBN	Clustering, Anomaly Detection, Data Compression, Image Generation
Reinforcement Learning	Reward-Based Interaction	Sequential Decision Making	Q-Learning, DQN, PPO, DDPG, SAC	Robotics, Autonomous Vehicles, Gaming, Resource Optimization

Overall, these three deep learning paradigms constitute the foundation of modern artificial intelligence systems. Supervised learning excels in predictive modeling using labeled datasets, unsupervised learning discovers hidden structures within unlabeled data, and reinforcement learning enables intelligent agents to learn optimal decision-making strategies through continuous interaction with their environment. Together, these techniques have significantly advanced the capabilities of intelligent systems across healthcare, agriculture, finance, cybersecurity, transportation, robotics, and numerous other application domains.

III. KEY DEEP LEARNING ALGORITHMS

Deep learning algorithms are based on artificial neural networks that consist of multiple hidden layers capable of learning complex patterns directly from large datasets. Unlike conventional machine learning algorithms, deep learning models automatically perform feature extraction, representation learning, and prediction through hierarchical processing. Depending on the application domain, different deep learning architectures have been developed to address various tasks such as image classification, speech

recognition, natural language processing, object detection, and time-series forecasting. This section discusses the fundamental deep learning algorithms, including Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Transformer Networks.

3.1 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs) are the foundation of deep learning and are inspired by the biological neural system of the human brain. An ANN consists of interconnected neurons organized into an input layer, one or more hidden layers, and an output layer. Each neuron receives weighted input values, applies an activation function, and forwards the computed output to the subsequent layer. During training, the network learns by minimizing the prediction error using the backpropagation algorithm and optimization techniques such as Stochastic Gradient Descent (SGD) or Adam.

The mathematical representation of an artificial neuron is given by:

$$y = f\left(\sum_{i=1}^n w_i x_i + b\right)$$

where:

1. $x_1, x_2, \dots, x_n$ represent the input features.
2. $w_1, w_2, \dots, w_n$ denote the corresponding weights.

3. b is the bias term.
4. $f()$ is the activation function.
5. y represents the predicted output.

Artificial Neural Networks are capable of modeling highly nonlinear relationships and are extensively applied in classification, regression, financial forecasting, medical diagnosis, and pattern recognition problems.

3.2 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are specialized deep learning architectures designed primarily for processing image and video data. CNNs automatically learn spatial features through convolution operations, eliminating the need for manual feature extraction. A typical CNN architecture consists of convolution layers, activation layers (ReLU), pooling layers, fully connected layers, and an output layer employing the Softmax activation function for classification.

The convolution operation can be expressed as:

Feature Map = Input Image * Kernel

where $*$ denotes the convolution operation, the kernel (filter) extracts important image features such as edges, textures, corners, and shapes.

Popular CNN architectures include:

1. LeNet
2. AlexNet
3. VGG16
4. GoogLeNet
5. ResNet
6. DenseNet
7. EfficientNet
8. MobileNet
9. Vision Transformer (ViT)

CNNs have achieved state-of-the-art performance in numerous computer vision tasks, including image classification, object detection, facial recognition, medical image analysis, remote sensing, and plant leaf disease detection.

3.3 Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNNs) are designed to process sequential and temporal data by incorporating feedback connections that enable information from previous time steps to influence future predictions. Unlike feedforward neural networks, RNNs maintain an internal hidden state that serves as memory,

allowing the network to model temporal dependencies within sequential data.

The hidden state at time step t is computed as:

$$h_t = f(W_h h_{t-1} + W_x x_t + b)$$

where:

1. x_t represents the current input.
2. h_{t-1} denotes the previous hidden state.
3. W_x and W_h are weight matrices.
4. b is the bias.
5. h_t is the updated hidden state.

Although RNNs effectively process sequential information, they suffer from the vanishing gradient problem when modeling long-term dependencies. This limitation led to the development of improved architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU).

Applications of RNNs include:

1. Speech recognition
2. Machine translation
3. Language modeling
4. Time-series prediction
5. Handwriting recognition

3.4 Transformer Networks

Transformer Networks represent one of the most significant breakthroughs in modern deep learning. Unlike RNNs, transformers process input sequences simultaneously using a self-attention mechanism, enabling efficient parallel computation and superior learning of long-range dependencies.

The attention mechanism is defined as:

$$\text{Attention}(Q, K, V) = \text{SoftMax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where:

1. Q = Query matrix
2. K = Key matrix
3. V = Value matrix
4. d_k = Dimension of the key vectors

Transformers form the foundation of modern Natural Language Processing (NLP) and Large Language Models (LLMs). Their ability to process long sequences efficiently has significantly improved performance in language understanding, text generation, machine translation, and multimodal learning.

Popular Transformer models include:

1. BERT

2. GPT
3. RoBERTa
4. T5
5. Vision Transformer (ViT)
6. LLaMA
7. Gemini

Transformer networks are widely applied in:

1. Machine translation
2. Chatbots
3. Text summarization
4. Question answering
5. Image classification
6. Code generation
7. Speech processing

Table 3.1 Comparison of Key Deep Learning Algorithms

Algorithm	Data Type	Major Strengths	Limitations	Typical Applications
Artificial Neural Network (ANN)	Structured Data	Learns nonlinear relationships	Overfitting, high computation	Classification, regression
Convolutional Neural Network (CNN)	Images and Videos	Automatic feature extraction	Requires large datasets	Computer vision, medical imaging
Recurrent Neural Network (RNN)	Sequential Data	Temporal dependency learning	Vanishing gradient	Speech recognition, NLP
Transformer Network	Text, Images, Audio	Parallel processing, long-range dependency modeling	High computational and memory requirements	Large Language Models, NLP, Vision

Overall, these deep learning algorithms constitute the core of modern artificial intelligence systems. Artificial Neural Networks provide the foundation for deep learning, Convolutional Neural Networks excel in visual recognition tasks, Recurrent Neural Networks effectively model sequential information, and Transformer Networks have revolutionized natural language processing and multimodal learning. Together, these architectures have significantly advanced intelligent systems across healthcare, agriculture, finance, cybersecurity, robotics, autonomous vehicles, and numerous other real-world applications.

IV. USE CASES OF DEEP LEARNING

Deep learning has become one of the most transformative technologies in artificial intelligence due to its ability to automatically learn complex patterns and hierarchical feature representations from large-scale datasets. Unlike conventional machine learning methods, deep learning models can efficiently process structured and unstructured data, including images, videos, speech, text, and sensor data, without requiring extensive manual feature engineering. Recent advances in Graphics Processing Units (GPUs), cloud computing, and large annotated datasets have significantly accelerated the adoption of deep learning across numerous application domains.

Today, deep learning plays a vital role in healthcare, finance, agriculture, transportation, cybersecurity, manufacturing, education, natural language processing, robotics, and smart cities. Some of the major use cases of deep learning are discussed below.

4.1 Healthcare

Healthcare is one of the most significant application areas of deep learning. Deep learning models assist healthcare professionals in disease diagnosis, medical image analysis, patient monitoring, drug discovery, and personalized medicine. Convolutional Neural Networks (CNNs) can automatically analyze medical images such as X-rays, CT scans, MRI scans, and ultrasound images to detect abnormalities with high accuracy. Deep learning has been successfully applied in the diagnosis of cancer, diabetic retinopathy, Alzheimer's disease, brain tumors, pneumonia, and cardiovascular diseases. Furthermore, wearable healthcare devices integrated with deep learning algorithms enable continuous monitoring of patients and early prediction of critical health conditions.

4.2 Finance

Deep learning has significantly improved financial decision-making by enabling intelligent analysis of large volumes of transactional and market data. Financial institutions employ deep learning models for fraud detection, algorithmic trading, credit scoring,

stock market prediction, customer behavior analysis, and financial risk assessment. Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformer models are widely used to analyze sequential financial data and predict future market trends. Deep learning algorithms also monitor real-time transactions to detect fraudulent activities and reduce financial losses.

4.3 Marketing

Deep learning has transformed digital marketing by providing intelligent customer analytics and personalized recommendation systems. Deep neural networks analyze customer demographics, browsing history, purchasing behavior, and social media interactions to understand consumer preferences and predict future buying behavior. These insights enable organizations to deliver personalized advertisements, optimize marketing campaigns, improve customer engagement, and increase sales. Recommendation systems employed by online platforms utilize deep learning to suggest products, movies, music, and services based on user interests.

4.4 Transportation

Deep learning plays a crucial role in intelligent transportation systems and autonomous vehicles. Self-driving cars rely on deep neural networks to process data collected from cameras, LiDAR, radar, and various sensors for real-time decision-making. Convolutional Neural Networks (CNNs) are used for object detection, traffic sign recognition, lane detection, and pedestrian identification, while Recurrent Neural Networks (RNNs) and Transformers assist in route planning and traffic prediction. These technologies significantly improve road safety, traffic management, and transportation efficiency.

4.5 Retail and E-Commerce

Retail and e-commerce industries extensively utilize deep learning to enhance customer experience, optimize inventory management, and improve business operations. Deep learning models analyze customer purchase history, seasonal demand, market trends, and inventory levels to forecast product demand and optimize stock management. Recommendation engines powered by deep learning provide personalized product suggestions, increasing customer satisfaction and sales. Additionally, deep

learning supports visual product search, automated customer service through chatbots, demand forecasting, and supply chain optimization.

4.6 Agriculture

Deep learning has emerged as a powerful technology in precision agriculture by enabling automated crop monitoring, disease diagnosis, yield prediction, and smart farming. Convolutional Neural Networks (CNNs) are widely used to identify plant diseases from leaf images, detect pests, estimate crop health, and classify agricultural products. Deep learning models also analyze satellite imagery, drone images, and sensor data to monitor crop growth, optimize irrigation, and improve agricultural productivity.

4.7 Natural Language Processing (NLP)

Deep learning has revolutionized Natural Language Processing by enabling machines to understand, generate, and translate human languages. Transformer-based architectures such as BERT, GPT, and T5 achieve state-of-the-art performance in language understanding and generation tasks. NLP applications include machine translation, document summarization, question answering, chatbots, sentiment analysis, and speech recognition.

V. CHALLENGES IN DEEP LEARNING

Despite the remarkable success of deep learning in solving complex problems across healthcare, finance, agriculture, transportation, natural language processing, and computer vision, several technical and practical challenges continue to limit its widespread adoption. Deep learning models require substantial computational resources, large-scale datasets, and careful model optimization to achieve high performance. Moreover, issues related to interpretability, privacy, fairness, and ethical decision-making remain major concerns for researchers and practitioners. Addressing these challenges is essential for developing reliable, transparent, and trustworthy deep learning systems.

5.1 Data Quality

Deep learning models are highly dependent on the quality and quantity of training data. Since these models learn complex feature representations directly from the input data, poor-quality datasets can

significantly degrade model performance. Incomplete, noisy, inconsistent, imbalanced, or biased data may result in inaccurate predictions and poor generalization on unseen data. Furthermore, deep learning models often require millions of labeled samples, making data collection and annotation both time-consuming and expensive.

To improve data quality, several preprocessing techniques are commonly employed, including data cleaning, missing value handling, normalization, standardization, outlier removal, feature scaling, image augmentation, and noise reduction. High-quality and diverse datasets are essential for developing robust deep learning models capable of performing reliably in real-world environments.

5.2 Interpretability

Although deep learning models often achieve state-of-the-art accuracy, they are frequently criticized for their lack of interpretability. Most deep neural networks function as "black-box" models because the decision-making process within multiple hidden layers is difficult to understand and explain. This lack of transparency reduces user trust, particularly in safety-critical applications such as healthcare, autonomous vehicles, finance, and legal systems, where understanding the reasoning behind model predictions is essential.

To improve transparency, researchers have developed Explainable Artificial Intelligence (XAI) techniques that provide visual and mathematical explanations of model decisions. Popular XAI methods include Gradient-weighted Class Activation Mapping (Grad-CAM), SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), attention visualization, and saliency maps.

5.3 Overfitting

Overfitting is one of the most common challenges encountered in deep learning. It occurs when a neural network learns the training data excessively well, including its noise and irrelevant patterns, resulting in poor performance on unseen test data. Overfitted models generally exhibit high training accuracy but low validation and testing accuracy, indicating poor generalization capability.

Several regularization techniques are employed to reduce overfitting and improve model generalization. These include dropout, batch normalization, early

stopping, L1/L2 regularization, data augmentation, transfer learning, cross-validation, model pruning, and appropriate hyperparameter tuning. Increasing dataset diversity and reducing model complexity can also help mitigate overfitting.

5.4 Ethical Concerns

The increasing deployment of deep learning systems in real-world applications has raised significant ethical concerns regarding fairness, accountability, transparency, privacy, and security. Deep learning models trained on biased or unrepresentative datasets may produce discriminatory outcomes, reinforcing existing social inequalities. For example, biased facial recognition systems may perform poorly for certain demographic groups, while biased recruitment or credit-scoring systems may result in unfair decision-making.

Privacy is another major concern because deep learning models often require access to large amounts of sensitive personal data. Protecting user privacy while maintaining model performance has become an active area of research through approaches such as Federated Learning, Differential Privacy, and Secure Multi-Party Computation.

5.5 Computational Complexity

Deep learning models typically require substantial computational resources for training and inference. Modern architectures such as Transformers and Large Language Models (LLMs) contain millions or even billions of parameters, demanding high-performance GPUs, TPUs, and large memory capacity. Training such models can consume considerable time and energy, increasing both financial and environmental costs.

Researchers are addressing this challenge through model compression, knowledge distillation, pruning, quantization, and efficient neural network architectures such as MobileNet, EfficientNet, and TinyML.

5.6 Data Privacy and Security

Deep learning applications frequently process sensitive personal information, including medical records, financial transactions, biometric data, and user behavior. Unauthorized access or data leakage may compromise user privacy and violate regulatory requirements.

These techniques enable collaborative model training while protecting sensitive data.

VI. CONCLUSION

Deep learning has emerged as one of the most significant advancements in artificial intelligence, revolutionizing the way complex problems are solved across numerous application domains. By automatically learning hierarchical feature representations from large-scale datasets, deep learning has significantly improved the accuracy and efficiency of intelligent systems compared with traditional machine learning techniques. The development of powerful computing resources, large annotated datasets, and advanced neural network architectures has accelerated the adoption of deep learning in both academic research and industrial applications.

This review has presented an overview of the fundamental deep learning techniques, including supervised learning, unsupervised learning, and reinforcement learning, along with the key deep learning algorithms such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Transformer Networks. These architectures have demonstrated remarkable success in solving challenging problems involving image recognition, speech processing, natural language understanding, sequential data analysis, and intelligent decision-making.

In conclusion, deep learning has become a transformative technology that is reshaping industries and society by enabling intelligent automation, accurate prediction, and data-driven decision-making. With continuous advancements in neural network architectures, computing infrastructure, and responsible AI practices, deep learning will continue to play a pivotal role in scientific research, industrial innovation, and the development of next-generation intelligent systems.

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