International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

A Comprehensive Survey of Deep Learning Models Across Diverse Application Domains

Satveer Kaur

Submitted: 01/06/2024 **Revised:** 12/07/2024 **Accepted:** 22/07/2024

Abstract: Deep learning, a significant domain of modern artificial intelligence, provides reliable solutions to an extensive scope of convoluted problems. This paper specifies a comprehensive outline of the most well-known deep learning models and the roles in a range of domains, including computer vision, cybersecurity, natural language processing, autonomous systems and healthcare. We look at the architecture, benefits, drawbacks, and performance of several models, comprising convolutional neural networks (CNNs), recurrent neural networks (RNNs), generative adversarial networks (GANs), transformers, and graph neural networks (GNNs). Comprehending a systematic literature review, we present perceptions into what way these models have transformed their relevant areas, converse evolving tendencies, and ascertain probable areas for further research.

Keywords: *Deep learning, artificial intelligence, domain applications, CNN, RNN, GAN, Transformer, GNN.*

1. Introduction

Deep learning is intensively transforming the arena of artificial intelligence (AI), letting robots to do chores with the equal or better ability as human beings in certain arenas. These models are predominantly apposite for roles including high-dimensional and amorphous data owing to their layered designs, which assist hierarchical data learning.

Through this paper, we look at a few deep learning models and how they're used in diverse areas. The purpose is to cognize how particular models impact the state of the art in every field and how they are well fitted to certain kinds of data and roles.

2. Deep Learning Models and Their Architectures

2.1 Convolutional Neural Networks (CNNs)

CNNs are frequently pertained to visual recognition problems due to their capability for spatial hierarchies within images (LeCun et al., 1998). They've been extremely significant in the refinement of image classification (Krizhevsky et al., 2012), object detection (Ren et al., 2015), and segmentation (Ronneberger et al., 2015).

P.G. Department of Computer Science, GSSDGS Khalsa College, Patiala, 147001, India

kcp.satveer@gmail.com

2.2 Recurrent Neural Networks (RNNs) and LSTMs

RNNs, specifically Long Short-Term Memory networks (LSTMs), are especially developed to realise temporal sequences and are extensively used in language modelling (Mikolov et al., 2010), speech recognition (Graves et al., 2013), and time-series forecasting.

2.3 Generative Adversarial Networks (GANs)

Developed by Goodfellow et al. (2014), GANs are comprised of a generator and a discriminator network that contend in a zero-sum game. They are widely pertained in image fusion, design transferal, and data expansion.

2.4 Transformers

Transformers (Vaswani et al., 2017) have altered natural language processing (NLP) with their attention mechanism. Models like BERT (Devlin et al., 2019) and GPT (Brown et al., 2020) have attained new contemporary outcomes in numerous NLP errands.

2.5 Graph Neural Networks (GNNs)

GNNs are exclusively designed to deal with graph-structured data and thus appropriate completely for drug discovery (Zitnik et al., 2018), recommendation system jobs (Wu et al., 2020), and social network analysis.

LSTMs are useful in management of electronic health records.

3.4 Autonomous Systems

Autonomous drones and cars are navigated with CNN-based perception and deep reinforcement learning (Bojarski et al., 2016). The models support decision-making in ambiguous environments, object detection, and navigation.

3.5 Cybersecurity

Deep learning improves cybersecurity by intrusion detection (Kim et al., 2016), malware classification (Huang and Stokes, 2016), and phishing detection. RNNs and GNNs are especially good at learning temporal and relational patterns in attack sequences.

4. Comparative Analysis

Every deep learning method has its strengths and weaknesses. CNNs are best with spatial data, and RNNs and LSTMs are best with sequential data. GANs are best on generative tasks but are plagued by training instability. Transformers are best with scalability and performance in NLP but use enormous computational resources. GNNs are best with relational data but are yet to reach maturity in scalability and expressiveness.

Model	Area Appropriateness	Primary Advantage	Limitation
CNN	Vision, Medical Imaging	Spatial feature extraction	Limited to grid-like data
RNN/LSTM	Speech, Time-series, EHR	Temporal dependencies	Vanishing gradient
GAN	Augmentation, Image generation	Realistic generation	Training instability
Transformer	NLP, Vision	Contextual understanding	High computational cost
GNN	Graph data, Drug discovery	Modelling relational structures	Scalability issues

5. Challenges and Future Directions

Even though deep learning models are successful, they also have issues of data privacy, model interpretability, and high computational needs. Future research is aimed at:

• **Explainable AI:** Creating understandable models to enable adoption and trust.

• **Efficient learning:** Procedures such as few-shot learning and federated learning attempt to reduce dependence on big labelled datasets.

• **Security and resilience:** Adversarial attack protection and guaranteeing model reliability in safety-critical use.

• **Cross-domain generalization:** Developing models that generalize across domains and tasks.

6. Conclusion

This paper described the landscape of deep learning models and their use in multiple fields. We concentrated on the architectural characteristics, strengths, and limitations of CNNs, RNNs, GANs, Transformers, and GNNs. The discussion highlights the need for model selection based on task objectives and data properties. Forthcoming developments in model proficiency, interpretability, and robustness will craft deep learning even more pervasive in tackling real-world problems.

References

[1] Bahdanau, D., Cho, K., & Bengio, Y. (2014). Neural machine translation by jointly learning to align and translate. arXiv:1409.0473.

[2] Bojarski, M., et al. (2016). End to end learning for self-driving cars. arXiv:1604.07316.

[3] Brown, T., et al. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems*, 33.

[4] Chen, L. C., et al. (2018). Encoder-decoder with atrous separable convolution for semantic image segmentation. *ECCV*.

[5] Devlin, J., et al. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. *NAACL*.

[6] Gawehn, E., Hiss, J. A., & Schneider, G. (2016). Deep learning in drug discovery. *Molecular Informatics*, 35(1), 3-14.

[7] Goodfellow, I., et al. (2014). Generative adversarial nets. *NeurIPS*.

[8] Graves, A., Mohamed, A. R., & Hinton, G. (2013). Speech recognition with deep recurrent neural networks. *ICASSP*.

[9] He, K., et al. (2016). Deep residual learning for image recognition. *CVPR*.

[10] Huang, W., & Stokes, J. W. (2016). MtNet: A multi-task neural network for dynamic malware classification. *Detection of Intrusions and Malware*.

[11] Kim, G., Lee, S., & Kim, S. (2016). A novel hybrid intrusion detection method integrating anomaly detection with misuse detection. *Expert Systems with Applications*, 41(4), 1690-1700.

[12] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. *NeurIPS*.

[13] LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11), 2278-2324.

[14] Litjens, G., et al. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, 42, 60-88.

[15] Liu, Y., & Lapata, M. (2019). Text summarization with pretrained encoders. *EMNLP*.

[16] Miotto, R., et al. (2016). Deep patient: An unsupervised representation to predict the future of patients from the electronic health records. *Scientific Reports*, 6(1), 1-10.

[17] Mikolov, T., et al. (2010). Recurrent neural network based language model. *Interspeech*.

[18] Pathak, D., et al. (2016). Context encoders: Feature learning by inpainting. *CVPR*.

[19] Redmon, J., et al. (2016). You only look once: Unified, real-time object detection. *CVPR*.

[20] Ren, S., et al. (2015). Faster R-CNN: Towards real-time object detection with region proposal networks. *NeurIPS*.

[21] Ronneberger, O., et al. (2015). U-Net: Convolutional networks for biomedical image segmentation. *MICCAI*.

[22] Socher, R., et al. (2013). Recursive deep models for semantic compositionality over a sentiment treebank. *EMNLP*.

[23] Vaswani, A., et al. (2017). Attention is all you need. *NeurIPS*.

[24] Wu, Z., et al. (2020). A comprehensive survey on graph neural networks. *IEEE Transactions on Neural Networks and Learning Systems*.

[25] Zitnik, M., et al. (2018). Modeling polypharmacy side effects with graph convolutional networks. *Bioinformatics*, 34(13), i457-i466.