Bodhi International Journal of
Research in Humanities, Arts and Science

Vol. 10 Special Issue 2 January 2026
E-ISSN: 2456-5571

Recent Trends in Deep Learning Techniques in Neural Networks

[1]S. Thanga Pandeeswari & [2]M. Shanmuga Eswari

[1]Assistant Professor, PG Department of Commerce, Sri Kaliswari College (A), Sivakasi, Tamil Nadu
[2]Assistant Professor, Department of Computer Science, Sri Kaliswari College (A), Sivakasi, Tamil Nadu

Open Access

Manuscript ID:
BIJ-SPL2-JAN26-MD-023

Subject: Computer Science

Received : 23.08.2025
Accepted : 11.01.2026
Published : 31.01.2026

DOI: 10.64938/bijsi.v10si2.26.Jan023

Abstract

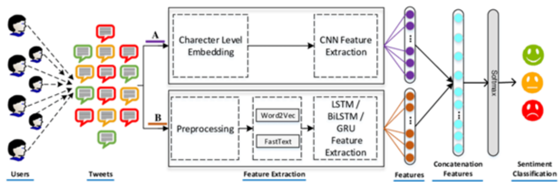
Current inclinations in deep learning implementing on huge information's and effortless data design combined with several soft computing algorithms and automated decision making as Artificial The above progressions brought innovative models to empower task performance lied on recent scenario and its outcome. This brought hybrid method to spot an image. Vision Transformer (ViT) enterprises with attention mechanisms for superior outcome. Next, Self-supervised learning drifted, where representations can acquire data from raw, and unlabelled. It reduced large volume of labelled data and refining their skill to put on knowledge to new circumstances. Natural language processing (NLP) models, such as GPT, T5, and BERT, are highly performed to drag the restrictions go beyond to understand and create a best. These progresses are smarter, malleable, and cross discipline artificial intelligence systems to shape the forthcoming deep learning study and applications.

Keywords: Convolutional, Neural Networks, NLP, Vision Transformer, Supervised

Methods

Hybrid Integrated Model

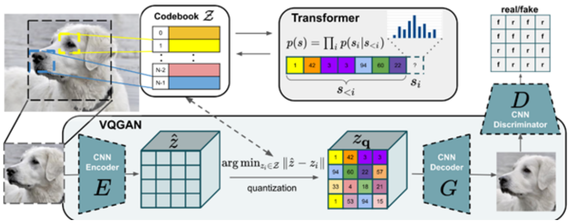
This provides a mode to generate a new domain from location of data to create weather, census and other kind of applications. Results show that adding deep learning networks to hybrid models can lead to better decisions on issues like safety and performance measures such as growth and employment. Hybrid models combine the strengths of symbolic AI and deep learning. They are a top-down approach to artificial intelligence and aim to create intelligent machines by using "high-level symbolic representations," as proposed by Allen Newell and Herbert A. Simon in their physical symbol system theory. Marcus Gary pointed out that soon, many people may question why deep learning took so long to incorporate the powerful tools of symbolic manipulation. Hybrid models can increase the speed, accuracy, and thoroughness of decision-making.



Hybrid Model Integration

Vision Transformer

The Vision Transformer, commonly referred to as ViT, is an image classification model developed by researchers at the University of Washington. This is cast-off in recognizing object, captioning of image, and analysing social media data. It has input, middle, and output layer. An input layer shields labelled images with sentiments negative, neutral, uncertain, sad, happy, or angry. Second layer recognises image objects. Output layer delivers an assertion score from the middle and input layers. This monitors several deep learning architectures, It uses pooling layers in association with multiple channels into one before passing the images to other models for classification. This transformers allows the design of models that can handle different input formats (images, text, and multimedia).

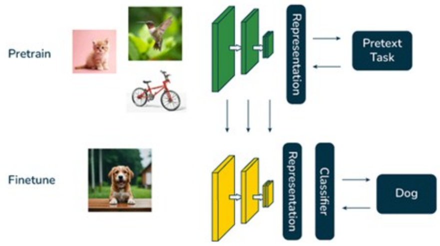


Vision Transformer

Self-Supervised Learning

This deep learning method enables automation by allowing models to learn from raw data without depending on labeled information.

Each part of the input can predict other parts. For example, it might forecast the future based on past data. In a self-supervised system, the input is labeled either by an intelligent agent or an external source. The output is also marked with a label that reflects the quality of the prediction. The algorithm used to train such a system aims to reduce the difference between the predicted labels and the actual labels.



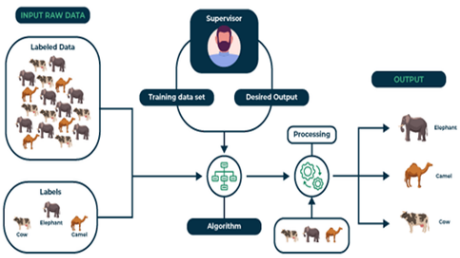
Self Supervised Learning

There are some popular learning techniques other than Self-Supervised Learning Algorithms as well:

- Supervised Learning
- Unsupervised Learning
- Semi-Supervised Learning
- Reinforcement Learning

Supervised Learning

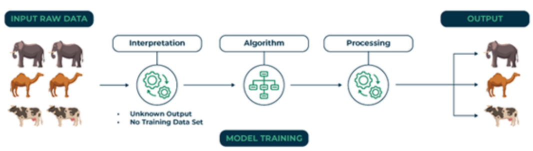
It uses labeled data where the model learns to predict outcomes based on known inputs and targets.



Supervised Learning

Unsupervised Learning

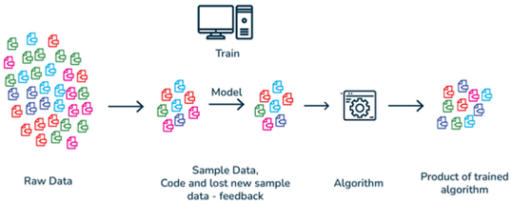
It works with unlabeled data, focusing on identifying patterns in the data.



Unsupervised Learning

Semi-Supervised Learning

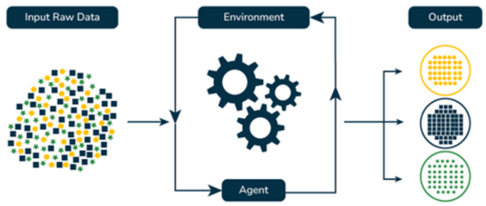
It uses a mix of labeled and unlabeled data.



Semi- Supervised Learning

Reinforcement Learning

It involves learning through trial and error in an environment to maximize rewards.



Reinforcement Learning

It is the variation in the quality of predictions made by a system based on different data instances. In self-supervised learning, two main types of errors can occur: bias and variance.

Bias refers to the model's tendency to overestimate or underestimate its predictions. Variance refers to the changes in prediction quality based on different data instances. A self-supervised learning system typically involves four stages: preprocessing, feature extraction, training, and testing.

Neuroscience Based Deep Learning

The human brain is highly complicated, with an endless capacity for learning. Deep learning has been a prominent approach for investigating how the brain works in recent years. Neuroscience-based deep learning is a type of ML that uses data from neuroscience experiments to train artificial neural networks. It allows researchers to develop models that better understand how the brain works.

Artificial neural networks constructed on computers are comparable to those seen in human brains. As a result of this formation, scientists and researchers have uncovered thousands of neurological remedies and ideas. Deep learning has provided neuroscience with the much-needed boost it has long needed. By way of the deployment of more strong, wide-ranging, and cutting-edge deep learning applications and clarifications. Dynamics of flexibility proportion have improved expressively.

Superior NLP Models

NLP is an emergent arena in AI to comprehend anthropoid linguistic model includes machine learning, and statistics. In context of finding different words for same is still under research. This is an incredulous by higher language model with millions of documents with greater complexity.

NLP applications

This uses computational dialectology, which is the learning of how etymological works based on various learning. This is attempt to gratify the feelings of orator’s or writers. This is progressed to convey interpreters, speech synthesizer, transcript recognizer and summarizer along with digital assistants to simplify the tasks.

Conclusion

In this article, highlighted some of the recent trends in deep learning. Deep learning techniques models have revolutionized the landscape of artificial intelligence, enabling breakthroughs across diverse domains such as computer vision, natural language processing, robotics, and healthcare. Their ability to automatically learn hierarchical representations from vast amounts of data has led to unprecedented performance levels in both academic and industrial settings. However, despite their success, challenges remain in areas such

Vol. 10 Special Issue 2 January 2026
E-ISSN: 2456-5571

as model interpretability, data efficiency, robustness, and ethical considerations. Recent developments, including hybrid model integration, self-supervised learning, Vision Transformers, neuroscience-inspired architectures, and high-performance NLP systems, are shaping the future of deep learning toward more generalizable, scalable, and human-aligned systems. As research continues to bridge gaps between biology, cognition, and computation, deep learning is poised to evolve into a more powerful, efficient, and trustworthy paradigm for intelligent systems.

References

1. Hassan, Saeed-Ul, Imran, Mubashir, Iqbal, Sehrish, Aljohani, Naif Radi and Nawaz, Raheel (2018) Deep context of citations using machine-learning models in scholarly full-text articles. Scientometrics, 117 (3). ISSN 0138-9130
2. PanelAli Abrishami, Sadegh Aliakbary (2019) Predicting citation counts based on deep neural network learning techniques ,journal of informatics, vol-13,issue-2,
3. M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin, S. Ghemawat, I. Goodfellow, A. Harp, G. Irving, M. Isard, Y. Jia, R. Jozefowicz, L. Kaiser, M. Kudlur, J. Levenberg, D. Mane, R. Monga, S. Moore, D. Murray, ´ C. Olah, M. Schuster, J. Shlens, B. Steiner, I. Sutskever, K. Talwar, P. Tucker, V. Vanhoucke, V. Vasudevan, F. Viegas, O. Vinyals, P. Warden, ´ M. Wattenberg, M. Wicke, Y. Yu, and X. Zheng. TensorFlow: Largescale machine learning on heterogeneous distributed systems. arXiv, 1603.04467, 2016.
4. D. Amodei, R. Anubhai, E. Battenberg, C. Case, J. Casper, B. Catanzaro, J. Chen, M. Chrzanowski, A. Coates, G. Diamos, E. Elsen, J. Engel, L. Fan, C. Fougner, T. Han, A. Hannun, B. Jun, P. LeGresley, L. Lin, S. Narang, A. Ng, S. Ozair, R. Prenger, J. Raiman, S. Satheesh, D. Seetapun, S. Sengupta, Y. Wang, Z. Wang, C. Wang, B. Xiao, D. Yogatama, J. Zhan, and Z. Zhu. Deep speech 2: End-to-end speech recognition in English and Mandarin. arXiv, 1512.02595, 2015.
5. D. Bahdanau, K. Cho, and Y. Bengio. Neural machine translation by jointly learning to align and translate. In International Conference on Learning Representations, ICLR, 2015. [5] M. G. Bellemare, Y. Naddaf, J. Veness, and M. Bowling. The arcad.
6. Y. Chen, T. Luo, S. Liu, S. Zhang, L. He, J. Wang, L. Li, T. Chen, Z. Xu, N. Sun, and O. Temam. DaDianNao: A machine-learning supercomputer. In Proceedings of the 47th International Symposium on Microarchitecture, 2014.
7. Y.-H. Chen, T. Krishna, J. Emer, and V. Sze. Eyeriss: An energy-efficient reconfigurable accelerator for deep convolutional neural networks. In International Solid-State Circuits Conference, ISSCC, 2016.
8. S. Chetlur, C. Woolley, P. Vandermersch, J. Cohen, J. Tran, B. Catanzaro, and E. Shelhamer. cuDNN: Efficient primitives for deep learning. arXiv, 1410.0759, 2014.
9. P. Chi, S. Li, C. Xu, T. Zhang, J. Zhao, T. Liu, Y. Wang, and Y. Xie. PRIME: A novel processing-in-memory architecture for neural network computation in reram-based main memory. In Proceedings of the 43rd International Symposium on Computer Architecture, ISCA, 2016.
10. F. Chollet. Keras: Theano-based deep learning library. https://keras.io, 2015.
11. Karpathy and L. Fei-Fei. Deep visual-semantic alignments for generating image descriptions. In Proceedings of the Conference on Computer Vision and Pattern Recognition, CVPR, 2015.
12. D. P. Kingma and M. Welling. Stochastic gradient VB and the variational auto-encoder. In Second International Conference on Learning Representations, ICLR, 2014.
13. Krizhevsky, I. Sutskever, and G. E. Hinton. ImageNet classification with deep convolutional neural networks. In Advances in neural information processing systems, NIPS, 2012.

14. Y. LeCun, C. Cortes, and C. J. Burges. The MNIST database of handwritten digits. http://yann.lecun.com/exdb/mnist/, 1998.
15. D. Liu, T. Chen, S. Liu, J. Zhou, S. Zhou, O. Teman, X. Feng, X. Zhou, and Y. Chen. PuDianNao: A polyvalent machine learning accelerator. In Proceedings of the Twentieth International Conference on Architectural Support for Programming Languages and Operating Systems, ASPLOS, 2015.
16. V. Mnih, K. Kavukcuoglu, D. Silver, A. Graves, I. Antonoglou, D. Wierstra, and M. Riedmiller. Playing atari with deep reinforcement learning. In NIPS Deep Learning Workshop, 2013.
17. V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, et al. Human-level control through deep reinforcement learning. Nature, 518(7540):529–533, 2015.
18. K. Ovtcharov, O. Ruwase, J.-Y. Kim, J. Fowers, K. Strauss, and E. S. Chung. Accelerating deep convolutional neural networks using specialized hardware. http://research.microsoft.com/apps/pubs/default.aspx?id=240715, 2015.
19. B. Reagen, P. Whatmough, R. Adolf, S. Rama, H. Lee, S. K. Lee, J. M. Hernandez-Lobato, G.-Y. Wei, and D. Brooks. Minerva: Enabling low- ´ power, highly-accurate deep neural network accelerators. In Proceedings of the 43rd International Symposium on Computer Architecture, ISCA, 2016.
20. Shafiee, A. Nag, N. Muralimanohar, R. Balasubramonian, J. Strachan, M. Hu, R. S. Williams, and V. Srikumar. ISAAC: A convolutional neural network accelerator with in-situ analog arithmetic in crossbars. In Proceedings of the 43rd International Symposium on Computer Architecture, ISCA, 2016.