IJITCE

ISSN 2347- 3657

International Journal of
Information Technology & Computer Engineering

Email : ijitce.editor@gmail.com or editor@ijitce.com

International Journal of
Information Technology & Computer Engineering

ISSN 2347–3657
Volume 10,Issue 4,Nov22

Deep Learning: A Comprehensive Overview on Techniques, Taxonomy,Applications and Research Directions

1 Ravikumar Kandru, 2 G.Manikanta,3 Nagaraju Thumu

Article Info

Received: 03-07-2022 Revised: 17 -08-2022 Accepted: 12-09-2022

Abstract

Deep learning (DL), a branch of machine learning (ML) and artificial intelligence (AI) is nowadays considered as a core technology of today's Fourth Industrial Revolution (4IR or Industry 4.0). Due to its learning capabilities from data, DL technology originated from artificial neural network (ANN), has become a hot topic in the context of computing, and is widely applied in various application areas like healthcare, visual recognition, text analytics, cybersecurity, and many more. However, building an appropriate DL model is a *challenging* task, due to the dynamic nature and variations in real-world problems and data. Moreover, the lack of core understanding turns DL methods into black-box machines that hamper develop- ment at the standard level. This article presents a structured and *comprehensive view* on DL techniques including a *taxonomy* considering various types of real-world tasks like supervised or unsupervised. In our taxonomy, we take into account deep networks for supervised or *discriminative learning*, unsupervised or *generative learning* as well as *hybrid learning* and relevant others. We also summarize *real-world application areas* where deep learning techniques can be used. Finally, we point out ten potential aspects for future generation DL modeling with *research directions*. Overall, this article aims to draw a big picture on DL modeling that can be used as a reference guide for both academia and industry professionals.

Keywords Deep learning · Artificial neural network · Artificial intelligence · Discriminative learning · Generativelearning · Hybrid learning · Intelligent systems

I. Introduction

In the late 1980s, the field of Machine Learning (ML) and Artificial Intelligence (AI) witnessed a surge in interest in neural networks owing to the development of various efficient learning methods and network structures . Some of these innovative methodsincluded multilayer perceptron networks trained using "Backpropagation" algorithms, self-organizing maps, and radial basis function networks. However, the research fervor surrounding neural networks declined over time. In 2006, the introduction of "Deep Learning" (DL) by Hinton et al. , based on the concept of artificial neural networks (ANN), marked a significant revival in neural network research. This resurgence is often referred to as the emergence of "new-generation neural networks," as deep networks, when appropriately trained, demonstrated substantial success in addressing various classification and regression challenges .Today, DL technology is a prominent subject within the fields of machine learning, artificial intelligence, data science, and analytics, owing to its adeptness at learning from provided data. Major corporations such as Google, Microsoft, Nokia, and others actively engage in its study, recognizing its potential in solving diverse classification and regression problems and datasets . Positioned as a subset of ML and AI, DL can be viewed as an AI function emulating the data processing capabilities of the human brain. The increasing global prominence of "Deep Learning" is evidenced by historical data collected from Google trends .

1. Assistant Professor, Department of CSE, RISE Krishna Sai Gandhi Group of Institutions, Ongole,
2.Associate Professor, Department of CSE, RISE Krishna Sai Gandhi Group of Institutions, Ongole,
3.Assistant Professor, Department of CSE, RISE Krishna Sai Gandhi Group of Institutions, Ongole.

ISSN 2347–3657
Volume 10,Issue 4,Nov22

Distinguished from standard machine learning, deep learning employs multiple layers to represent data abstractions for constructing computational models. While deep learning entails longer training periods due to a high number of parameters, its testing phase is relatively quick compared to other machine learning algorithms . Despite the Fourth Industrial Revolution's (4IR or Industry 4.0) focus on technology-driven automation and intelligent systems, DL technology, derived from ANN, has emerged as one of the key technologies in achieving these objectives . A typical neural network comprises numerous interconnected processing elements or neurons, each generating a sequence of real-valued activations for the target outcome.

DL-based neural network technology finds widespread applications across variousfields, including healthcare, sentiment analysis, natural language processing, visual recognition, business intelligence, cybersecurity, and many more, as outlined later in this paper. Although DL models find successful applications in these various domains, constructing an appropriate deep learning model remains a challenging task, primarily due to the dynamic nature and variability of real-world problems and data. Moreover, DL models are often regarded as "black-box" machines, posing challenges for standard deep learning research and applications.

II. Why Deep Learning in Today's Research and Applications?

The contemporary focus of the Fourth Industrial Revolution (Industry 4.0) primarily revolves around technology-driven automation and the development of intelligent systems, applicable across various sectors such as smart healthcare, business intelligence, smart cities, cybersecurity intelligence, and more . Within the realm of security technologies, the dramatic advancements in deep learning techniques have positioned them as a robust solution for unraveling complex architectures within high-dimensional data. Consequently, DL techniques have the potential to be instrumental in constructing intelligent data-driven systems tailored to contemporary requirements, owing to their exceptional learning capabilities derived from historical data. Thus, DL has the power to transform not only the world but also the daily lives of individuals through its automation prowess and experiential learning.

Given its robust learning capabilities, DL technology holds relevance within the domains of artificial intelligence [103], machine learning [97], and data science equipped with advanced analytics , all of which are well-established areas in computer science, especially within today's intelligent computing landscape. To delve further, we initially discuss the role of deep learning in the context of AI, examining how DL technology correlates with these computing domains.

The Position of Deep Learning in AI:

In contemporary discourse, the terms artificial intelligence (AI), machine learning (ML), and deep learning (DL) are often used interchangeably to describe systems or software exhibiting intelligent behavior. Figure illustrates the positioning of deep learning in relation to machine learning and

International Journal of
Information Technology & Computer Engineering
ISSN 2347–3657
Volume 10,Issue 4,Nov22

artificial intelligence. According to the illustration, DL constitutes a vital subset within the broader domains of AI and ML, driving innovation and development in intelligent computing.

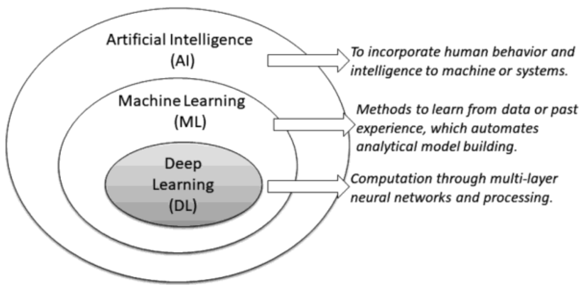

Fig. 2 An illustration of the position of deep learning (DL), comparing with machine learning (ML) and artifcial intelligence (AI)

aims to imbue machines or systems with human-like intelligence and behavior , whereas ML is a means to enable systems to learn from data or experiences, thereby automating the construction of analytical models . DL, on the other hand, represents a category of learning methods that leverages multi-layer neural networks and processing to derive insights from data. The term "Deep" in deep learning denotes the concept of utilizing multiple levels or stages of data processing to construct data-driven models.

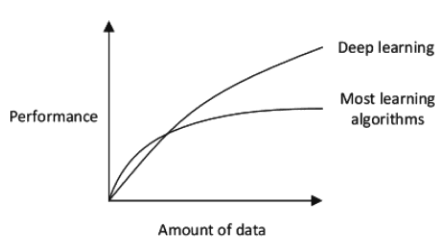

Fig. 3 An illustration of the performance comparison between deeplearning (DL) and other machine learning (ML) algorithms, where DL modeling from large amounts of data can increase the perfor- mance

Consequently, DL can be recognized as a fundamental technology within the AI domain, serving as a frontier for artificial intelligence and contributing to the development of intelligent systems and automation. Moreover, it propels AI to an advanced stage termed "Smarter AI." Given DL's capability to learn from data, it also shares a strong association with the realm of "Data Science" . Data science typically encompasses the entire process of uncovering meaning and insights from data within a specific problem domain, where DL methods play a crucial role in facilitating advanced analytics and intelligent decision-making .

In summary, DL technology possesses the capability to enact transformative changes in our world, particularly as a potent computational engine, thus contributing significantly to the realm of technology-driven automation and intelligent systems.

III. Understanding Various Forms of Data

A profound comprehension and representation of data are pivotal in constructing a data-driven intelligent system for specific application areas, given that DL models learn from data. Data in the real world can manifest in various forms, such as sequential data, which encompasses any data where the order holds significance, including sequences like text streams, audio fragments, video clips, and time-series data. Furthermore, image or 2D data is represented as a matrix, essentially a 2D array of

International Journal of
Information Technology & Computer Engineering
ISSN 2347–3657
Volume 10,Issue 4,Nov22

numbers, symbols, or expressions organized in rows and columns, with essential characteristics like matrix, pixels, voxels, and bit depth. On the other hand, tabular data, which constitutes a logical and systematic arrangement of data in rows and columns resembling a database table, is another form commonly encountered. Deep learning models are adept at efficiently learning from tabular data, enabling the development of data-driven intelligent systems.

IV. DL Properties and Dependencies

The workflow of a DL model generally aligns with the processing stages of machine learning modeling. In Figure 4, a deep learning workflow is illustrated for resolving real-world problems, comprising three key steps: data comprehension and preprocessing, DL model construction and training, and validation and interpretation. Notably, in contrast to ML modeling, feature extraction in the DL model is automated rather than manual .

While machine learning techniques such as K-nearest neighbor, support vector machines, decision tree, random forest, naive Bayes, linear regression, and association rules are commonly applied across various domains , the DL model involves methods such as convolutional neural networks, recurrent neural networks, autoencoders, deep belief networks, among others, each briefly discussed along with their potential application areas in Section 3. Subsequently, the discussion delves into the essential characteristics and interdependencies of DL techniques.

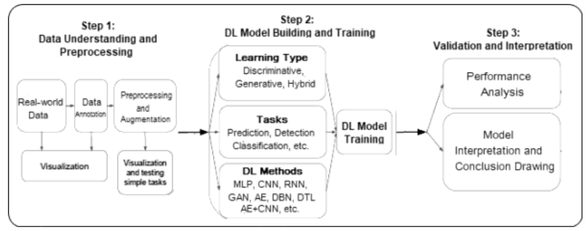

Fig. 4 A typical DL workflow to solve real-world problems, which consists of three sequential stages (i) data understanding and preprocessing

Several crucial factors need to be considered before delving into DL modeling for real-world applications. These include data dependencies, hardware requirements, the feature engineering process, model training and execution time, and the challenge of interpretability.

Deep learning heavily relies on extensive datasets for building effective data-driven models within a specific problem domain. Insufficient data can lead to poor performance, prompting the need for alternative standard machine learning algorithms . Furthermore, due to the substantial computational demands during training, GPUs are often preferred over CPUs to optimize performance, making high-performance hardware an essential requirement for DL tasks .

Distinct from traditional machine learning, DL emphasizes automated feature extraction, thereby reducing the time and effort typically associated with constructing a feature extractor for each problem . However, the prolonged training time for DL algorithms, owing to the significant number of parameters, is a critical consideration, with training sessions lasting longer, sometimes

ISSN 2347–3657
Volume 10,Issue 4,Nov22

spanning weeks, while testing times remain relatively short .

Interpretability poses a notable challenge for DL models, as they are often perceived as "black-box" systems, making it difficult to explain how specific results were obtained. In contrast, rule-based machine learning techniques provide transparent logic rules that are easily interpretable for humans . Balancing this trade-off between interpretability and performance is crucial when selecting the appropriate approach.

DL's exceptional performance in handling large datasets has been highlighted, illustrating its capacity to process extensive features effectively, leading to the construction of robust data-driven models. When developing and training DL models, utilizing specialized libraries and resources like PyTorch and TensorFlow, which offer essential functions and pre-trained models, proves instrumental in streamlining the implementation and building process .

In essence, while DL presents unparalleled advantages in processing vast amounts ofdata and extracting complex features, understanding and managing its specific requirements and limitations are crucial for successful implementation and utilization.

V. Deep Reinforcement Learning (DRL)

Reinforcement learning takes a diferent approach to solving the sequential decision-making problem than other approaches we have discussed so far. The concepts of an environment and an agent are often introduced first in reinforcement learning. The agent can perform a series of actions in the environment, each of which has an impact on the environment's state and can result in possible rewards (feedback) - "positive" for good sequences of actions that result in a "good" state, and "negative" for bad sequences of actions that result in a "bad" state. The purpose of reinforcement learning is to learn good action sequences through interaction with the environment, typically referred to as a policy. Deep reinforcement learning (DRL or deep RL) integrates neural networks with a reinforcement learning architecture to allow the agents to learn the appropriate actions in a virtual environment, as shown in Figure. In the area of reinforcement learning, model-based RL is based on learning a transition model that enables for modeling of the environment without interacting with it directly, whereas model-free RL methods learn directly from interactions with the environment. Q-learning is a popular model-free RL technique for determining the best action-selection policy for any (fnite) Markov Decision Process (MDP). MDP is a mathematical framework for modeling decisions based on state, action, and rewards .In addition, Deep Q-Networks, Double DQN, Bi-directional Learning, Monte Carlo Control, etc. are used in the area. In DRL methods it incorporates DL models, e.g. Deep Neural Networks (DNN), based on MDP principle , as policy and/ or value function approximators. CNN for example can be used as a component of RL agents to learn directly from

International Journal of
Information Technology & Computer Engineering
ISSN 2347–3657
Volume 10,Issue 4,Nov22

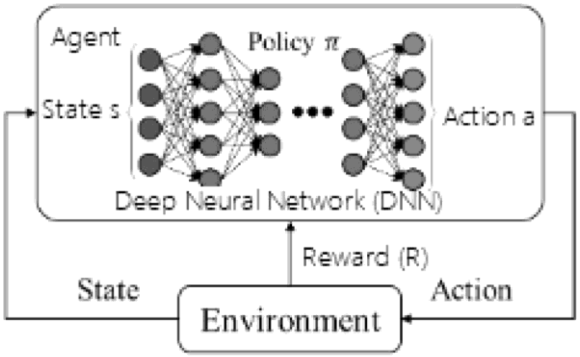

Fig. 5 Schematic structure of deep reinforcement learning (DRL) highlighting a deep neural network

VI. Deep Learning Application Summary

During the past few years, deep learning has been success- fully applied to numerous problems in many application areas. These include natural language processing, senti- ment analysis, cybersecurity, business, virtual assistants, visual recognition, healthcare, robotics, and many more. In Fig.5, we have summarized several potential real-world application areas of deep learning. Various deep learning techniques according to our presented taxonomy in that includes discriminative learning, generative learning, as well as hybrid models, discussed earlier, are employed in these application areas. we have also summarized

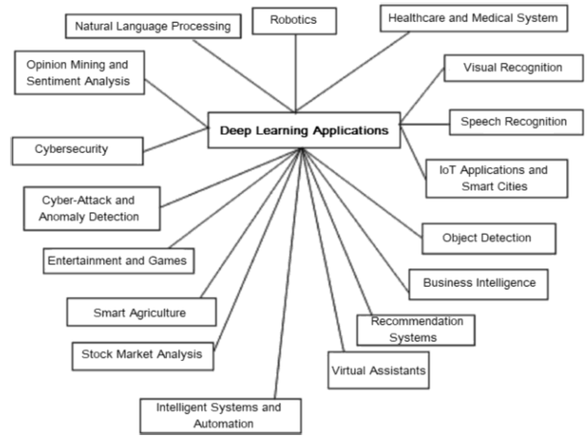

Fig. 6 Several potential real-world application areas of deep learning

CONCLUSION

Then, the key algorithms in this area, as well as deep neural network modeling in various dimensions are explored. For this, we have also presented a taxonomy considering the variations of deep learning tasks and how they are used for different purposes. In our compre- hensive study, we have taken into account not only the deep networks for supervised or discriminative learning but also the deep networks for unsupervised or generative learning, and hybrid learning that can be used to solve a variety of real-world issues according to the nature of problems.

Deep learning, unlike traditional machine learning and data mining algorithms, can produce extremely high-level data representations from enormous amounts of raw data. As a result, it has provided an excellent solution to a variety ofreal-world problems. A successful deep learning technique must possess the relevant data-driven modeling depending on the characteristics of raw data. The sophisticated learn- ing algorithms then need to be trained through the collecteddata and knowledge related to the target application before the system can assist with intelligent decision-making. Deep learning has shown to be useful in a wide range of applica- tions and research areas such as healthcare, sentiment analy- sis, visual recognition, business intelligence, cybersecurity, and many more that are summarized in the paper.

Finally, we have summarized and discussed the chal- lenges faced and the potential research directions, and future aspects in the area. Although deep learning is considereda black-box solution for many applications due to its poor reasoning and interpretability, addressing the challenges or future aspects that are identified could lead to future genera- tion deep learning modeling and smarter systems. This can also help the researchers for in-depth analysis to produce more reliable and realistic outcomes. Overall, we believe that our study on neural networks and deep learning-based advanced analytics points in a promising path and can be uti- lized as a reference guide for future research and implemen- tations in relevant application domains by both academic and industry professionals.

References

1. Abadi M, Barham P, Chen J, Chen Z, Davis A, Dean J, Devin Ma, Ghemawat S, Irving G, Isard M, et al. Tensorflow: a systemfor large-scale machine learning. In: 12th {*USENIX*} Symposium on operating systems design and implementation ({*OSDI*} 16), 2016; p. 265–283.
2. Abdel-Basset M, Hawash H, Chakrabortty RK, Ryan M. Energy-net: a deep learning approach for smart energy man- agement in iot-based smart cities. IEEE Internet of Things J. 2021.
3. Aggarwal A, Mittal M, Battineni G. Generative adversarial net- work: an overview of theory and applications.Int J Inf Manag Data Insights. 2021; p. 100004.
4. Al-Qatf M, Lasheng Y, Al-Habib M, Al-Sabahi K. Deep learning approach combining sparse autoencoder with svm for network intrusion detection. IEEE Access. 2018;6:52843–56.
5. Ale L, Sheta A, Li L, Wang Y, Zhang N. Deep learning based plant disease detection for smart agriculture. In: 2019 IEEE Globecom Workshops (GC Wkshps), 2019; p. 1–6. IEEE.
6. Amarbayasgalan T, Lee JY, Kim KR, Ryu KH. Deep autoencoder based neural networks for coronary heart disease risk prediction. In: Heterogeneous data management, polystores, and analytics for healthcare. Springer; 2019. p. 237–48.
7. Anuradha J, et al. Big data based stock trend prediction using deep cnn with reinforcement-lstm model. Int J Syst Assur Eng Manag. 2021; p. 1–11.
8. Aqib M, Mehmood R, Albeshri A, Alzahrani A. Disaster man- agement in smart cities by forecasting traffic plan using deep learning and gpus. In: International Conference on smart cities, infrastructure, technologies and applications. Springer; 2017. p. 139–54.
9. Arulkumaran K, Deisenroth MP, Brundage M, Bharath AA. Deep reinforcement learning: a brief survey. IEEE Signal Process Mag. 2017;34(6):26–38.
10. Aslan MF, Unlersen MF, Sabanci K, Durdu A. Cnn-based trans-fer learning-bilstm network: a novel approach for covid-19 infec- tion detection. Appl Soft Comput. 2021;98:106912.

International Journal of
Information Technology & Computer Engineering
ISSN 2347–3657
Volume 10,Issue 4,Nov22

11. Bu F, Wang X. A smart agriculture iot system based on deep rein- forcement learning. Futur Gener Comput Syst. 2019;99:500–7.