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Analysis of AI Algorithm Development: From Machine Learning to Deep Learning

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Abstract: The development of Artificial Intelligence (AI) is currently very rapid, but there is still much confusion regarding the differences and evolution of the main algorithms, namely machine learning (ML) and deep learning (DL). This study aims to analyze the development of AI algorithms conceptually and technically from conventional ML to DL, and to provide a structured understanding of the paradigm shift in AI development. The method used is a systematic literature study of 10 recent scientific articles discussing aspects of ML and DL algorithms. The results of the analysis show that ML relies on manual feature extraction with the advantages of computational efficiency and interpretability, while DL is able to process large and complex data automatically with better performance, although it requires high computing resources and faces interpretability challenges. The discussion also identifies the main challenges that AI still faces as well as innovation opportunities to overcome these limitations. In conclusion, a deep understanding of the evolution of AI algorithms is essential as a foundation for the development of more adaptive, effective, and transparent AI technology in the future.

Keywords: Artificial Intelligence; Machine Learning; Deep Learning

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1. Introduction

The rapid development of digital technology in the last two decades has driven major transformations in various sectors of life [20]. One of the key elements in this transformation is Artificial Intelligence (AI), which is now the main driver of the data-driven industrial revolution. AI is no longer limited to the realm of academic research, but has been widely applied in fields such as industrial automation, recommendation systems, autonomous vehicles, and natural language processing. Nowadays, AI tools can be found across a wide range of sectors, including education, entertainment, healthcare, public service delivery, smart cities, and virtual companion services. The success of AI in solving various complex problems cannot be separated from significant advances in the underlying algorithms [9]. Therefore, an analysis of the development of AI algorithms, especially from machine learning to deep learning approaches, is important to understand the direction of the evolution of this technology and its implications for the future of artificial intelligence. Despite the increasing popularity of AI, there are still many misunderstandings in its use, both in academia and industry. Terms such as Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) are often used interchangeably without adequate conceptual understanding of the differences and relationships between the three [8]. This not only creates ambiguity in scientific communication but also results in a lack of accuracy in choosing an algorithmic approach that is appropriate to the problem at hand. The lack of in-depth understanding of the evolution of AI algorithms also results in confusion [6] in the process of developing and implementing artificial intelligence-based systems, especially in adjusting the complexity of the method to the specific needs of the application. Therefore, it is important to critically examine the differences in characteristics, working principles, and strengths and limitations of each approach in the spectrum of AI algorithms. The history of the development of artificial intelligence (AI) shows significant evolution in the approaches and technologies used. Initially, AI was developed through rule-based systems or expert systems, which relied on a set of logical rules explicitly defined by humans [11]. An early example of this approach is the ELIZA program developed in 1966 by Joseph Weizenbaum [5], which simulated human conversation through predetermined rules. Over time, the limitations of rule-based systems in dealing with the complexity and variability of data led to the emergence of machine learning (ML) approaches in the 1990s [12]. ML allows systems to learn from data and improve performance without explicit programming. Early applications of ML included handwriting recognition, spam filtering, and speech recognition, demonstrating the ability of ML to identify patterns in complex data [3]. Further advancements in AI occurred with the emergence of deep learning (DL) in the 2010s, a branch of ML that uses multi-layered artificial neural networks to model complex patterns in data [10]. DL has revolutionized applications such as image recognition, natural language processing, and autonomous driving. One of the significant achievements of DL was the development of AlphaGo by

DeepMind, which defeated the world champion in the game of Go, demonstrating the ability of DL to handle complex strategic tasks.

Although the development of Artificial Intelligence (AI) has made rapid progress, there is still a gap in academic studies that systematically discuss the evolution of algorithms, especially the transition from Machine Learning (ML) to Deep Learning (DL) [16]. Many studies focus on the application or performance of certain algorithms in specific application contexts, but few provide a comprehensive analysis of the methodological paradigm shift in AI algorithm development. This leads to a lack of comprehensive understanding of the dynamics of AI technology development itself. In fact, a clear mapping of the advantages, limitations, and challenges of each algorithmic approach is very important for determining the direction of research and the development of more adaptive and efficient systems. Therefore, an in-depth study is needed that not only compares the technical characteristics of ML and DL, but also examines their implications for computational needs, data quality, and interpretability of results within the framework of the development of AI as a whole. Based on the urgency and gaps that have been described, this study aims to analyze the development of Artificial Intelligence (AI) algorithms conceptually and technically, with a focus on the transition from conventional machine learning (ML) to deep learning (DL) approaches. This study is expected to provide a structured understanding of the paradigm shift in AI development, both in terms of theory and its application. By comparing the characteristics, strengths, and challenges of each approach, this study will help clarify the direction of methodological evolution that is occurring in the field of AI. In addition, the results of this study are also expected to be a theoretical basis for the development of AI technology research and innovation in the future, so that it can make a significant contribution to the development of intelligent systems that are more effective, efficient, and adaptive to the needs of the times.

2. Related Work

The development of Artificial Intelligence (AI) algorithms, particularly the transition from Machine Learning (ML) to Deep Learning (DL), has been the subject of numerous studies across different domains. Prior research has mostly focused on evaluating the performance of specific algorithmic implementations within domain-specific applications, such as ecology (Pichler & Hartig, 2023), healthcare (Brnabic & Hess, 2021), robotics (Soori et al., 2023), and mental health (Arji et al., 2023). These studies highlight how ML and DL have contributed to improvements in prediction accuracy, automation, and decision-making processes.

Several works have provided comprehensive reviews of deep learning technologies. For example, Schmidhuber (2014) laid the foundational understanding of neural network-based learning systems, while Alom et al. (2018) traced the historical evolution of DL methods starting from AlexNet. Alzubaidi et al. (2021) and Sarker (2021) further classified the architecture, applications, and technical challenges of DL, particularly the use of convolutional neural networks (CNN), recurrent neural networks (RNN), and generative adversarial networks (GAN).

Conversely, ML approaches continue to be widely discussed in traditional contexts due to their interpretability and lower computational costs. Brnabic & Hess (2021) and Xu et al. (2025) provide insights into ML usage in real-world clinical decision systems and environmental modeling respectively. However, these methods are often limited by the need for manual feature engineering and their lower performance on complex or unstructured datasets.

Despite these contributions, there is a lack of integrative work that systematically contrasts the two paradigms — ML and DL — across technical, theoretical, and practical dimensions. Studies such as Uc Castillo et al. (2025) and Soori et al. (2023) begin to address this gap, but they often emphasize domain-specific results rather than exploring the underlying methodological shifts. Thus, the current study aims to fill this gap by providing a comparative and conceptual analysis of AI algorithm development using a systematic literature review (SLR) approach, guided by the PRISMA framework.

3. Methods

This study employed a systematic literature review (SLR) approach following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework. The literature search was conducted using Scopus, IEEE Xplore, ScienceDirect, and Springer databases. The keywords used included 'Machine Learning', 'Deep Learning', 'AI algorithm evolution', and 'ML vs DL'. The initial search yielded 325 articles. After applying inclusion criteria (English language, published between 2014–2025, peer-reviewed) and exclusion criteria (non-academic sources, articles without clear methodology), 10 articles were selected. The selection process is illustrated in the PRISMA diagram (Figure 1).

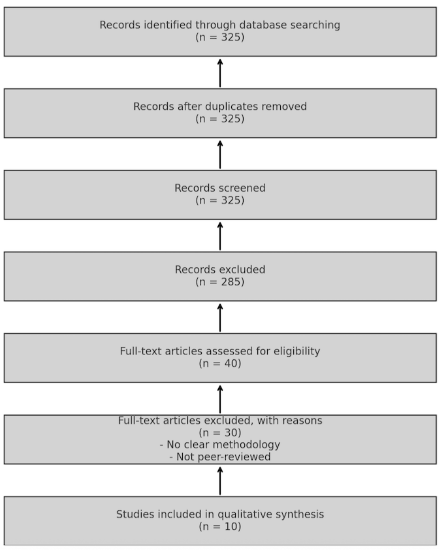

Figure 1. PRISMA diagram

4. Results and Discussion

4.1 Overview of Reviewed Articles

To support the analysis of the development of Artificial Intelligence algorithms from machine learning (ML) to deep learning (DL), researchers conducted a review of a number of relevant and credible current scientific literature. This review includes articles published in reputable journals and internationally recognized scientific databases. The selection of articles is based on the suitability of the topic, contribution to the understanding of the evolution of AI algorithms, and its relevance to the research focus. The list of articles analyzed is presented in Table 1 below.

Table 1. List of Scientific Articles Related to the Development of AI Algorithms

No.	Article Title	Author and Year	Main Focus
1	A systematic review of Machine Learning and Deep Learning approaches in Mexico: challenges and opportunities	(Uc Castillo et al., 2025)	Systematic review of ML and DL in different fields in Mexicoo
2	Machine learning and deep learning—A review for ecologists	(Pichler & Hartig, 2023)	Applications of ML and DL in ecology and conservation
3	From Detection to Decision: A Systematic Literature Review of AI and Machine Learning Evolution in Methane Modelling	(Xu et al., 2025)	Evolution of AI and ML in methane modeling
4	Artificial intelligence, machine learning and deep learning in advanced robotics	(Soori et al., 2023)	Transformation of AI, ML, and DL in advanced robotics
5	Systematic literature review of machine learning methods used in the analysis of real-world data for patient-provider decision making	(Brnabic & Hess, 2021)	Systematic review of ML in clinical decision support systems
6	Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions	(Sarker, 2021)	Comprehensive review of DL techniques, taxonomy, applications, and research directions
7	Review of deep learning: concepts, CNN architectures, challenges, applications, future directions	(Alzubaidi et al., 2021)	Review of DL, CNN architectures, challenges,

			applications, and future directions
8	A systematic literature review and analysis of deep learning algorithms in mental disorders	(Arji et al., 2023)	Systematic review of current DL methods for mental health monitoring
9	The History Began from AlexNet: A Comprehensive Survey on Deep Learning Approaches	(Alom et al., 2018)	Comprehensive survey of DL approaches since AlexNet
10	Deep Learning in Neural Networks: An Overview	(Schmidhuber, 2014)	Comprehensive review of DL in neural networks

In this study, a review of 10 leading scientific articles discussing the development of Artificial Intelligence (AI) algorithms with a focus on the transition from Machine Learning (ML) to Deep Learning (DL) was conducted. The articles were selected based on the relevance of the topic, the validity of the source, and their contribution to the conceptual and technical understanding of the evolution of AI algorithms. From all the articles, there is a clear classification regarding the themes and algorithm approaches raised. Most of the articles review in depth the techniques and applications of Deep Learning such as (Alom et al., 2018; Alzubaidi et al., 2021; Sarker, 2021; Schmidhuber, 2014), highlighting the development of increasingly complex neural network architectures and superior big data processing capabilities compared to conventional ML. Meanwhile, several articles also discuss Machine Learning more broadly, including traditional approaches and their integration in clinical, ecological, and robotic systems (Brnabic & Hess, 2021; Pichler & Hartig, 2023; Soori et al., 2023).

In terms of temporality, the distribution of publication years of articles shows a significant upward trend in AI-related research, especially from 2018 to 2025. This reflects the acceleration of research and adoption of AI technology in various fields. The earliest article (Schmidhuber, 2014) provides a fundamental theoretical foundation for deep learning, while recent articles such as Xu et al., (2025) and Uc Castillo et al., (2025) describe the application and evolution of AI technology in increasingly specific and multidisciplinary contexts. Overall, the reviewed literature reflects the development of the algorithmic paradigm from ML to DL, showing a shift in research focus from manual feature-based learning methods to deep learning models that can extract data representations automatically and adaptively. These findings provide an important basis for understanding how AI is evolving and are expected to help clarify the direction of algorithm development and its application in the future..

4.2 Machine Learning Algorithm Trends

4.2.1 Analysis of Machine Learning (ML) Algorithm Development

Conventional Machine Learning (ML) algorithms that are widely discussed in the literature include methods such as decision trees, support vector machines (SVM), k-nearest neighbors (K-NN), and logistic and linear regression. The main characteristic of these algorithms is their ability to perform classification and prediction based on features that have been manually determined by domain experts. These methods are generally supervised learning and focus on modeling explicit relationships between input and output variables. The main advantages of conventional ML algorithms lie in the simplicity of implementation and relatively high model interpretability, making them easy to understand and apply in various contexts, including clinical decision support systems [7] and ecological applications [13]. In addition, conventional ML algorithms usually require lower computational resources compared to deep learning, making them a good choice for small to medium-sized datasets.

4.3 Deep Learning Algorithm Trends

However, the weaknesses of these algorithms have also been highlighted in a number of studies. One is the heavy reliance on manually extracted features, which can result in suboptimal performance if the selected features are not representative enough [18]. In addition, conventional ML is prone to overfitting problems when the model is too complex for limited training data, so that its performance decreases when tested on new data [17]. Some algorithms are also less effective in processing very large data or those with complex structures, such as image or audio data. Another technical challenge that often arises is the limitation in handling non-linear and heterogeneous data automatically, which then drives the need for more adaptive and complex learning approaches, such as deep learning. This constraint is one of the main driving factors for the paradigm shift from traditional ML to DL that is able to extract features automatically and deeply. Thus, the development of conventional ML algorithms shows significant strengths in certain contexts, but also limitations that motivate innovation in more sophisticated and flexible learning methods to accommodate the complexity of today's data.

4.3.1 Analysis of Deep Learning (DL) Algorithm Development

Deep Learning (DL) is a branch of machine learning that focuses on learning using multi-layered artificial neural networks. The basic concept of DL involves processing data through several hidden layers that allow the model to extract features automatically and hierarchically from raw data. Some of the main architectures in DL that are widely discussed in the literature are Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Generative Adversarial Networks (GAN).

4.4 Comparative Analysis of ML and DL

CNN is particularly effective for processing image and visual data, thanks to its ability to capture spatial patterns using convolution and pooling layers. RNN and its variants such as LSTM are particularly useful for sequential data such as text, sound, and time signals, as they can maintain contextual information in the data sequence. Meanwhile, GAN introduces an innovative generative approach to generating new data that resembles the original data, with broad applications ranging from image synthesis to data quality improvement [1].

The main advantage of DL over conventional ML lies in its ability to effectively process large and complex data without the need for manual feature extraction. DL models can learn more abstract and rich data representations, resulting in superior performance, especially in the fields of image recognition, natural language processing, and signal processing [14]. In addition, DL can adapt to various types of data with different structures, expanding its application in various domains. However, DL also faces several significant obstacles. One of the main problems is the very high computational requirements, both in terms of hardware and training time, which requires the use of GPUs and expensive resources [21]. In addition, DL models tend to be "black boxes" due to the complexity of the architecture and the large number of parameters, so model interpretability and transparency are still important challenges, especially for applications in fields that require high accountability such as health and law [7]. Considering these advantages and obstacles, DL continues to be an active research field with various innovations to improve computational efficiency and model transparency. The evolution of DL marks a major paradigm shift in AI development that enables more sophisticated and adaptive applications of the technology to real-world needs.

4.4.1 Comparison of Machine Learning and Deep Learning Paradigms

The development of Artificial Intelligence shows a significant methodological and technological shift from conventional Machine Learning (ML) approaches to Deep Learning (DL). Traditional ML relies on manually extracted features and simple statistical models to make predictions, while DL uses layered neural networks that are able to automatically extract features and learn hierarchical data representations [2]. This paradigm shift has important implications for the effectiveness and efficiency of AI. DL significantly improves AI's ability to process large and complex data, such as images, videos, and natural language, which have previously been difficult to accommodate by conventional ML algorithms. This can be seen in the increase in performance in various application fields, such as object detection in medical images, speech recognition, and recommendation systems [14]. In addition, DL provides greater flexibility in model development, allowing for better adaptation to data variability and application context.

4.5 Gaps and Research Opportunities

Table 2. Comparative Summary of ML vs. DL

Feature	Machine Learning (ML)	Deep Learning (DL)
Feature Engineering	Manual, requires domain knowledge	Automatic through neural layers
Data Requirement	Works well with small-medium datasets	Requires large datasets
Interpretability	High	Low ("black box")
Computational Cost	Low to moderate	High, requires GPUs
Flexibility	Limited to structured data	Flexible with images, audio, text
Training Time	Shorter	Longer
Performance	Moderate, depends on features	Generally superior in complex tasks

However, computational efficiency is a major challenge for DL compared to ML. ML is often more resource-efficient and easier to interpret, and is therefore still preferred in situations with limited data or high transparency needs [7]. On the other hand, DL requires more powerful hardware and longer training times, although with more accurate results in many cases.

An example of an application that illustrates this performance difference can be seen in the field of medical image recognition. A study by Pichler & Hartig (2023) showed that DL methods (e.g. CNN) significantly outperform traditional ML in terms of disease detection and classification accuracy from radiological images, thanks to their ability to recognize very complex and subtle patterns. Meanwhile, ML is still widely used for tabular data and relatively simple prediction problems, where interpretability and prediction speed are more important. Overall, the shift from ML to DL reflects the evolution of AI technology that is oriented towards increasing performance through greater complexity and computational capacity, with a trade-off in resource requirements and model transparency. The choice between ML and DL in practice depends on the application context, data availability, and interpretability and efficiency needs.

Although the development of Artificial Intelligence, especially in the fields of Machine Learning (ML) and Deep Learning (DL) algorithms, has shown rapid progress, a number of major challenges remain

significant obstacles in the development of AI. One critical issue is the enormous computational requirements of DL models, which poses cost, energy consumption, and limited access to technology for many institutions and developers [21]. In addition, the problem of model interpretability remains a major challenge, where the complexity of deep neural networks makes prediction results difficult to explain transparently, hampering the trust and adoption of AI in critical sectors such as health and law [7]. In addition, the limited availability of quality and representative data is also a significant obstacle, especially in domains with sensitive or difficult-to-obtain data. The problem of data bias that can lead to discrimination and unfair outcomes is an important ethical concern in the development of AI [17].
However, these challenges open up vast opportunities for research and innovation. Research is focusing on developing more efficient and energy-efficient DL algorithms, such as lightweight models and network compression techniques (model pruning) that aim to reduce the need for computational resources without sacrificing performance [2]. In addition, interpretability and explainable AI (XAI) approaches are emerging as a rapidly growing research field to improve the transparency and accountability of AI models [14]. Predictions of future AI algorithm evolution trends based on current literature suggest that AI will increasingly move towards hybrid models that combine the advantages of ML and DL and integrate with other technologies such as federated learning and edge computing to address privacy and efficiency issues [18]. In addition, research on AI that can learn with little data (few-shot learning) and continuous learning is expected to be a major focus to deal with the ever-changing dynamics of real-world data. Overall, although there are still many challenges to overcome, there are huge opportunities for innovation that can drive AI to become more efficient, transparent and adaptive, making this technology increasingly relevant and having a positive impact in various areas of life.

4. Conclusion

This article has comprehensively analyzed the development of Artificial Intelligence (AI) algorithms from conventional machine learning (ML) to deep learning (DL). This development shows a significant paradigm shift marked by DL's ability to handle large and complex data automatically, in contrast to ML which still relies on manual feature extraction. Although DL offers higher performance advantages, challenges such as large computational requirements and low model interpretability are still major obstacles. On the other hand, ML remains relevant especially for applications with limited resource requirements and high transparency. Literature analysis also reveals that the future of AI will be greatly influenced by innovations in more efficient and transparent models, as well as the integration of various approaches to overcome existing limitations. Thus, a deep understanding of the evolution of AI algorithms is important as a foundation for the development of more adaptive and effective technologies in the future.

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Conflict of Interest Statement

The authors declare that there are no conflicts of interest related to this study.

Ethical Approval

This study did not involve human participants or the collection of primary data. Therefore, ethical approval was not required.

Data Availability Statement

No primary dataset was generated or used for this study. The study is based entirely on previously published literature.

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