SELF-LEARNING ALGORITHMS – HISTORY, ADVANCEMENTS, APPLICATIONS, CHALLENGES, AND FUTURE DIRECTIONS

Dr. Kiranpal Singh Virk*

*Associate Professor
Guru Nanak Khalsa College,
Yamuna Nagar, Haryana, INDIA
Email id: Kiranpal.virk@gmail.com

DOI: 10.5958/2278-4853.2022.00384.6

ABSTRACT

Self-learning algorithms, also known as autonomous learning algorithms or unsupervised learning algorithms have emerged as a powerful and innovative approach in the field of artificial intelligence. These algorithms possess the ability to learn from unstructured and unlabeled data, enabling machines to autonomously identify patterns, make informed decisions, and continuously improve their performance over time. In this review, we provide an overview of the advancements, challenges, and future directions in self-learning algorithms. We begin by introducing and discussing the historical development of self-learning algorithms, tracing their origins from artificial neural networks to the recent breakthroughs in deep learning and reinforcement learning. Next, we explore the present status of research in self-learning algorithms and ongoing advancements in algorithmic efficiency, scalability, interpretability, and the integration of self-learning algorithms with other domains such as natural language processing, computer vision, and robotics. Additionally, we address the ethical considerations associated with the deployment of self-learning algorithms, including bias, fairness, accountability, and privacy. Furthermore, we review the latest applications of self-learning algorithms across diverse industries, including healthcare, finance, autonomous systems, natural language processing, and cyber security. We highlight how these algorithms are revolutionizing various domains, improving disease diagnosis, driving automated trading strategies, enhancing autonomous vehicles, advancing language processing applications, and fortifying cyber security defences.

Finally, we identify the challenges and future directions in self-learning algorithms. We discuss the need for more explainable and interpretable models, as well as the importance of addressing ethical concerns to ensure responsible deployment. We also explore emerging research areas such as lifelong learning, transfer learning, and federated learning [2][10], which hold promise for advancing the capabilities of self-learning algorithms.

KEYWORDS: *Self-Learning Algorithms, Deep Learning, AI.*

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