



Artificial intelligence and neuroscience: A systematic review

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Abstract

In critical fields like medicine and healthcare, the transparency and comprehensibility of machine learning and artificial intelligence systems hold immense importance in garnering trust in their outcomes. Errors stemming from these systems, such as incorrect diagnoses or treatments, bear the potential for serious, even life-threatening repercussions for patients. Consequently, Artificial Intelligence (AI) has emerged as a pivotal area of investigation, focusing on unraveling the opaque nature of intricate and challenging-to-comprehend machine learning models. While human expertise can enhance the accuracy of these models, comprehending the inner workings of these models during their training phase can prove challenging, if not impossible. In our research, we identified 211 articles published in 2023 and delved into 20 of them to examine the application of these methodologies within the medical domain.

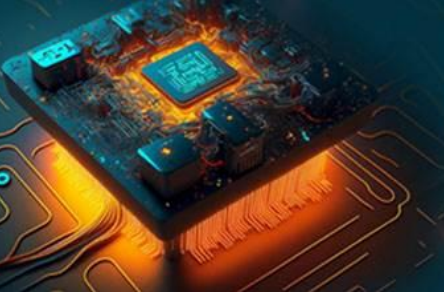
Key words: Machine learning, Artificial intelligence, Neuroscience, Neural networks

1. Introduction

Deep Neural Networks (DNNs) excel in image classification tasks, often outperforming human domain experts. In biomedical fields, there's a revived interest in employing AI techniques for imaging classification and segmentation [1]. Convolutional Neural Networks (CNNs) stand as leading models for image classification and segmentation [2], although encoder-decoder transformer architectures have also emerged [3–5]. Image segmentation in medical imaging involves delineating regions of interest, like lesions, by labeling every pixel to group similar constituent objects together. Classification assigns labels such as benign/malignant or normal/pneumonia/COVID-19 to medical images for binary or multi-class problems. Biomedical images come from diverse modalities like X-rays and ultrasounds, crucial for disease diagnosis and management (e.g., using fundus images for detecting eye diseases) [6].

The democratization of AI allows domain experts to apply machine learning algorithms without extensive knowledge of underlying algorithms. AI aids biomedical imaging by discerning intricate details (e.g., tumor size, texture) superior to human observers like radiologists [7], potentially transforming radiological diagnosis [8].

The brain, housing over a hundred billion neurons with myriad synapses, is the body's most complex organ. Brain tumors, notably gliomas, pose significant health threats, with increasing morbidity. Gliomas encompass various types originating from glial cells and present grave



symptoms like seizures, headaches, and behavioral changes [9-11]. Accurate localization and recognition of gliomas through brain tumor segmentation significantly impact diagnosis, treatment planning, and prognosis [12-14].

Decades of research have unraveled the biological and molecular underpinnings of gliomas, advancing diagnostic and therapeutic methods. Understanding genetic changes informs brain tumor grading, heredity, and targeted therapies using genomic data. Imaging techniques, especially MRI, play a pivotal role in diagnosing and monitoring brain tumors [13,14]. MRI-based examinations guide surgical interventions like minimally invasive surgery, enabling precise tumor removal while minimizing damage to healthy tissue. Brain tumor segmentation, altering MRI representations to pinpoint multiple tumor regions, aids prognosis and survival prediction, typically classifying tumor regions into Enhancing Tumor (ET), Tumor Core (TC), and Whole Tumor (WT) [15-20].

This review aims to introduce common techniques, elucidate fundamental concepts, and exemplify neuroscientific research applications in brain tumor imaging.

2. Literature review

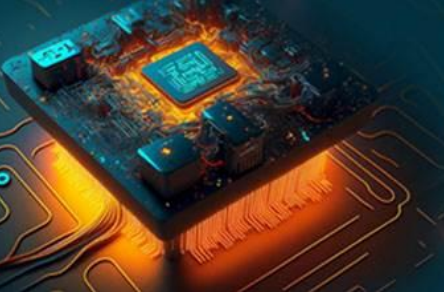
2.1. Artificial intelligence

The term "artificial intelligence" (AI) lacks a precise definition and generally refers to computer systems crafted to imitate human intelligence, striving to perform tasks within the human capability. AI resides within computer science but intersects closely with diverse research domains like data science, machine learning, and statistics. The potential of AI in scientific fields largely stems from its knack for unveiling structures within extensive datasets and leveraging these insights to make predictions or execute tasks. These systems possess unique strengths that complement human abilities. For instance, AI adeptly identifies patterns in intricate, high-dimensional data, serving as a powerful aid rather than a replacement for human researchers. The majority of modern AI systems rely on various forms of artificial neural networks (ANNs), drawing inspiration from the organization of the nervous system [21-22].

Subdivisions within artificial intelligence align with intended applications (diagnostic versus predictive), required inputs (supervised versus unsupervised learning), or the mathematical foundations of approaches used (linear versus non-linear, symmetric versus non-symmetric). Diagnostic versus predictive AI involves distinguishing whether an AI, when analyzing an image of a mole, can determine if it's cancerous or likely to become cancerous. Specialized techniques exist for both scenarios, though the overarching principles and challenges remain constant. An exploratory approach aiming to define mole subtypes might employ unsupervised learning, discovering groups without predefined categories, which may or may not correlate with benign or malignant properties. Conversely, a supervised approach actively seeks to differentiate cancerous from benign moles, learning from labeled datasets categorized as "cancerous" or "noncancerous" [23].

2.2. Unsupervised learning

Unsupervised learning encompasses a range of techniques that operate independently of predetermined outcomes. For instance, modern evolutionary trees rely on clustering genetic



similarities, where the final tree structure was initially unknown and solely emerges from the algorithm's underlying principles. These methods aim to uncover patterns of symmetry, order, or inherent structure within data [24].

Commonly used unsupervised learning methods include dimensionality reduction techniques like principal component analysis [25], hierarchical clustering such as Ward or Neighbour-joining [26-27], fast and heuristic algorithms like k-means ideal for large datasets [28], and density-based approaches like DBSCAN (density-based spatial clustering of applications with noise) [29]. There's no inherent superiority among these methods; their performance depends on the underlying structure of the data. The choice of method is contingent upon the specific characteristics and nature of the dataset being analyzed.

2.3. Supervised learning

Supervised learning relies on a labeled training dataset with known outcomes or classifications, such as images of moles paired with information regarding their malignancy. While it excels in uncovering non-linear and non-symmetrical relationships, its core concept of optimizing a function using a given training dataset can lead to overfitting or bias adjustment issues that may not be immediately apparent [30].

In its simplest manifestation, supervised machine learning can take the form of multiple linear regression, which can then be substituted with regularized linear regression models for controlling model complexity, or nonlinear regression models when dictated by the data's nature.

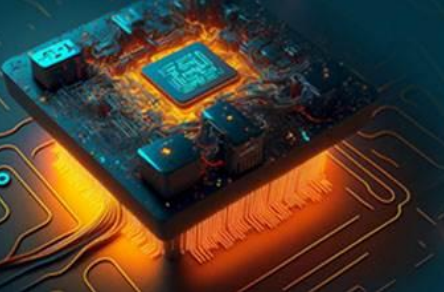
The recent substantial advancements in various fields, including facial detection, complex image processing tasks, and protein folding, along with foundational technologies like ChatGPT, have largely stemmed from the utilization of complex, non-linear, and non-symmetrical methods. Examples of such methods include Support Vector Machines [31], k-nearest neighbors [32], Hidden Markov Models [33], and Markov Chain Monte Carlo methods [34]. These techniques are founded on distinct mathematical models and assumptions, each demonstrating excellence in diverse domains.

Among supervised machine learning models, neural networks [35] have garnered immense attention, especially with the evolution of Deep Learning [36], a variant of neural networks. The focus on neural networks has been propelled by their widespread applicability and performance in various tasks, making them a cornerstone in the domain of supervised learning.

2.4. Neural networks and deep learning

Neural networks, developed to mimic biological processes akin to evolutionary algorithms, comprise interconnected nodes (perceptrons) organized into layers—input, hidden, and output—forming the simplest form of this model [37]. The network's complexity, and the potential for overfitting, is determined by the number of nodes in the hidden layer. Each node, akin to a synapse, forwards a signal based on input signals, similar to a post-synaptic potential either reaching the activation threshold at the axon hillock or not.

Recent breakthroughs in machine learning have largely been propelled by deep learning, a technique leveraging neural networks with multiple hidden layers and a vast number of nodes ranging from hundreds to billions. Each layer serves as a level of abstraction, and the



algorithms enable the network to autonomously determine and refine its structure [38]. Deep learning has surpassed many traditional AI techniques and underpins numerous remarkable achievements, such as the general-purpose utilization seen in models like ChatGPT and its successor, GPT-4 [39], as well as complex scientific tasks like protein folding [40]. However, despite its successes, deep learning isn't a universal solution; in many real-world scenarios, classical machine learning models, such as tree-based models, can outperform them depending on the dataset structure [40].

3. Previous studies

This section conducts a comprehensive statistical analysis for brain tumor segmentation methods. In our study, we identified 211 articles published 2023 and analyzed 20.

Table 1: Summary of previous research

	Authors	Method		Authors	Method
1	Chun Chou et al [42]	PBPK	11	Zhang et al [52]	Deep Learning
2	Monirul et al [43]	MobileNet	12	Farajzadeh et al [53]	Deep Learning
3	Zhang et al [44]	Machine learning	13	Ren et al [54]	ANN
4	Anaya-Isaza et al [45]	Cross-Transformer	14	Ruba et al [55]	Deep Learning
5	Sharma et al [46]	CNN	15	Ranjbarzadeh et al [56]	CNN
6	Tripathy et al [47]	CNN	16	Fernando & Toskos [57]	Deep Learning
7	Patil & Kirange [48]	SCNN	17	Raghuram & Hanumanthu [58]	SDNN
8	Chakrabarty & Mahajan [49]	CNN	18	Talukder et al [59]	Deep Learning
9	Alemu et al [50]	SVM	19	Shyamala & Brahmanada [60]	Regression Neural Network
10	Yaqub et al [51]	ALCResNet	20	Rezai [61]	CNN

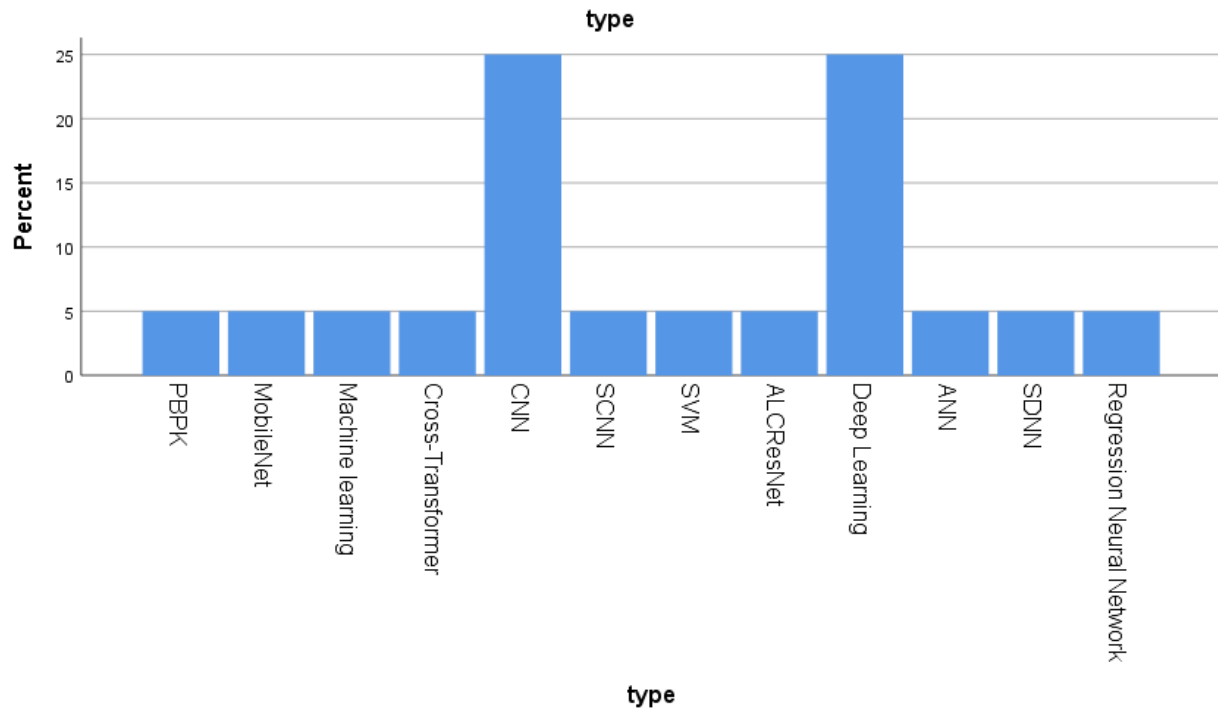
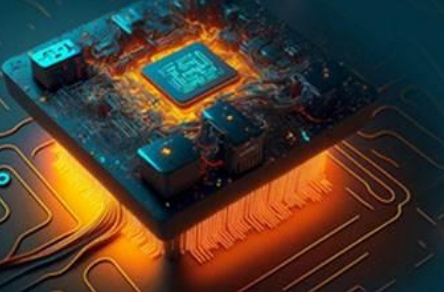


Figure 1: Frequency of using each method

4. Conclusions

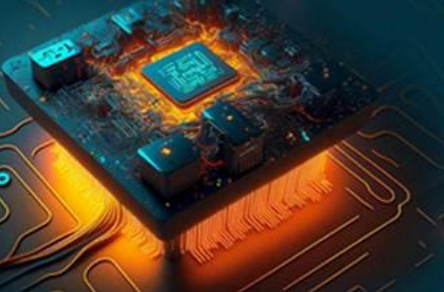
Since the onset of AI research in the mid-20th century, the human brain has been a fundamental source of inspiration for crafting artificial intelligence systems. This stems from the belief that the brain serves as a tangible model of comprehensive intelligence, exhibiting abilities like perception, planning, and decision-making, making it an enticing blueprint for AI design. This review, based on discussions from the 2020 International Symposium on Artificial Intelligence and Brain Science, delves into how mechanistic, structural, and functional elements inspired by the brain are utilized to innovate and enhance existing AI systems. Specifically, this approach has led to the creation of sophisticated high-dimensional deep neural networks, incorporating hierarchical architectures reminiscent of those observed in the brain. These networks showcase remarkable capabilities in tasks such as visual object recognition and memory-based cognitive functions. Furthermore, advancements in AI have contributed to progress within the realm of neuroscience. This article aims to introduce the latest methods in brain tumor detection, leveraging insights from AI and its intersection with brain-inspired approaches to improve diagnostic techniques in this critical medical field.

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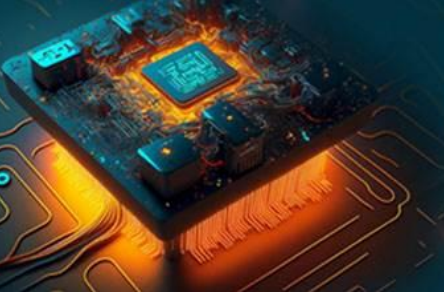
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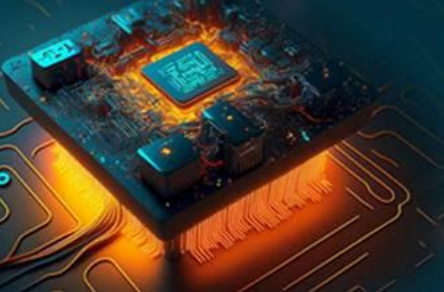
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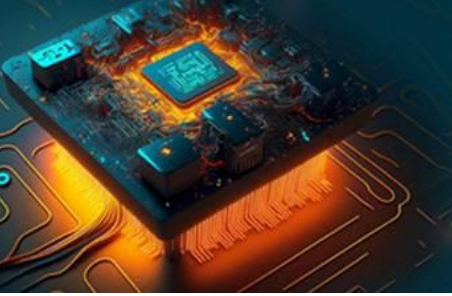
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