Targeted analysis of artificial intelligence and neuroscience in each other's development

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Abstract

These days, the world of artificial intelligence (AI) has expanded a lot; So that it includes mobile phones that are in the hands of most people in the society to humanoid robots that can behave completely like a human. Today, artificial intelligence has expanded and empowered so much that in some tasks it works even better, faster and more accurately than the human brain, an issue that has worried many activists in this field about the future of humans. Despite all these rightful concerns, practically all the countries of the world are trying to take a step towards improving artificial intelligence by creating more accurate computer systems, and they are not trying to prevent its progress! In fact, what encourages us to expand and improve the performance of artificial intelligence is the variety of services that artificial intelligence provides to us humans. 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.

Keywords: Artificial intelligence, machine learning, neural networks, neuroscience.

1. Introduction

One of the most common types of deep neural networks is known as Convolutional Neural Networks (CNN). CNN combines learned features with input data and uses two-dimensional convolution layers, and this architecture is suitable for processing two-dimensional data such as images. CNNs do not require manual feature extraction, so you do not need to identify the features used for image classification. CNN works by extracting features directly from images. The corresponding properties are not predefined. These networks are trained while and this training is done by a set of images. The ability to automatically extract features makes deep learning models very accurate for computer vision tasks such as object classification. Convolutional Neural Networks or CNNs learn to recognize different features of an image using tens or hundreds of hidden layers. Each hidden layer increases the complexity of the learned image features. For example, the first hidden layer can learn how to detect edges, and the last layer learns how to detect more complex shapes, specifically the shape of the object we're trying to detect. In general, CNNs in each layer recognize more detailed features from an image and finally draw conclusions. If it is a question of distinguishing a flower or a car or other devices from each other, it sees and analyzes a large number of images of flowers, cars, etc., and then makes a decision.

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. Convolutional Neural Networks (CNNs) stand as leading models for image classification and segmentation , although encoder-decoder transformer architectures have also emerged . 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) .

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 , potentially transforming radiological diagnosis.

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. Accurate localization and recognition of gliomas through brain tumor segmentation significantly impact diagnosis, treatment planning, and prognosis .

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 . 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) .

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

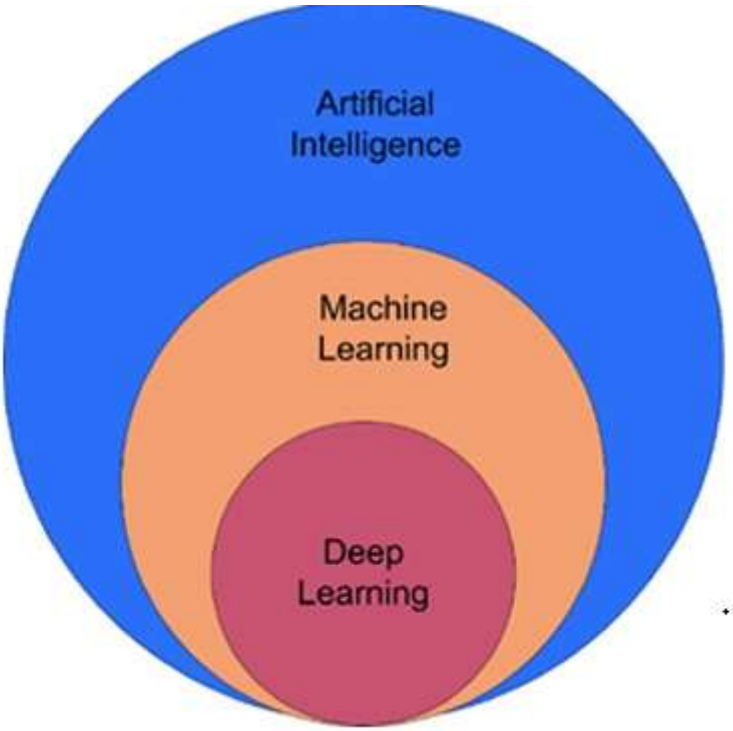

Figure 1: Architecture of deep neural networks

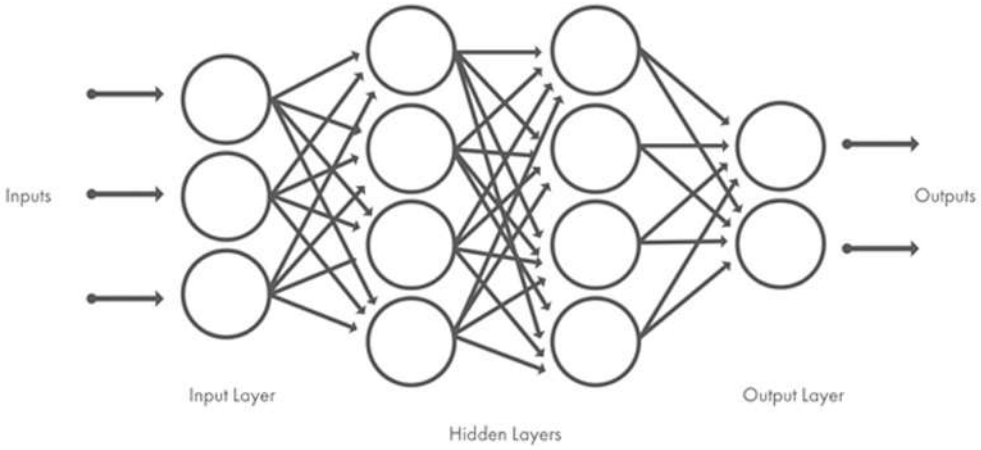

Figure 2: Hierarchical operations of extraction

2. Literature review

2.1.Artificial intelligence

When most people hear the term "artificial intelligence," the first thing they usually think of is robots. The reason for this thought is movies and novels that tell stories about human-like machines that destroy the earth with their appearance. But these stories are far from the truth. In fact, artificial intelligence or AI is based on the principle that human intelligence can be defined in such a way that a machine can easily imitate it and perform human tasks, from the simplest to the most complex. In other words, the main purpose of AI is to imitate human cognitive activities. So far, researchers and developers have made surprisingly rapid strides in simulating activities such as learning, reasoning, and perception to the point where they can be precisely defined. Some believe that we may soon see the development of systems that exceed the human capacity to learn or reason about anything. But others are pessimistic; Because they believe that all cognitive activities are accompanied by judgments that are subject to human experience. On the other hand, as technology advances, the previous criteria that defined AI become obsolete.

Artificial intelligence is a branch of computer science that aims to create systems that can imitate human intelligence and problem-solving abilities. Artificial intelligence (AI) does this by collecting massive amounts of data, processing it, and learning from its past data. This is while a computer program usually needs human intervention to fix bugs and improve processes. Since the beginning of creating the definition of AI, that is, in the 50s, this technology has seen various ups and downs and its complexity and capabilities have been added day by day. Expert systems, natural language processing, speech recognition, machine learning and machine vision are specific applications and types of AI. The history of Ai dates back to ancient times when the concept of intelligent inanimate objects was explored. Over the centuries, various thinkers and inventors contributed to the development of AI concepts. In the late 19th and early 20th centuries, seminal work on programmable machines and neural networks paved the way for modern computers. The term "Artificial intelligence" was used for the first time in a conference at Dartmouth College in 1956; Where the pioneers of Ai presented the first artificial intelligence-based application. Over the following decades, significant advances were made in Ai, but general AI became difficult to achieve, leading to periods known as "Ai winters"; The period when the government and industry support for this field decreased. In the late 1990s, the artificial intelligence renaissance occurred due to the increase in computing power and the explosion of data. Advances in natural language processing (NLP), computer vision, robotics, and machine learning were observed, leading to significant milestones. IBM's Deep Blue product was one of these milestones; Because he defeated the world chess champion. The 2000s saw further advances in artificial intelligence with the launch of various products and services, including voice assistants, recommendation engines, and self-driving cars. The 2010s saw a steady stream of AI advances; Among them are the victories of artificial intelligence systems in game shows, the creation of generative adversarial networks, the launch of deep learning frameworks and the implementation of artificial intelligence-based systems for medical diagnostics. In the current decade (2020), Generative AI has become prominent and enables the generation of new content in response to requests. Language models such as ChatGPT-3,

Google's Bard, and Microsoft's Megatron-Turing NLG, which borrows part of its name from Alan Turing, have shown impressive capabilities, but still have limitations such as illusions or biased responses.

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 .

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" .

2.2. Unsupervised learning

Unsupervised learning is a machine learning technique in which machine learning algorithms are used to analyze and cluster unlabeled data sets. These algorithms, without the need for human intervention, discover hidden patterns or different groups in the data. To better understand unsupervised learning, consider the following example. A baby lives in a family that has a pet dog. The baby knows the pet dog without being told anything beforehand. A few weeks later, a family friend brings a dog to their home. The infant has never seen the dog before, but recognizes many characteristics associated with dogs (for example, ears, eyes, walking on all fours) and therefore knows that this creature is like their own pet dog. He recognizes the new animal as a dog. This example is exactly an example of unsupervised learning. The infant learns from the data that dogs have certain characteristics. If this learning was observed, their family friend would tell the baby that it was a dog to learn.

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 .

Commonly used unsupervised learning methods include dimensionality reduction techniques like principal component analysis , hierarchical clustering such as Ward or Neighbour-joining , fast and heuristic algorithms like k-means ideal for large datasets , and density-based approaches like DBSCAN (density-based spatial clustering of applications with noise) . 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.

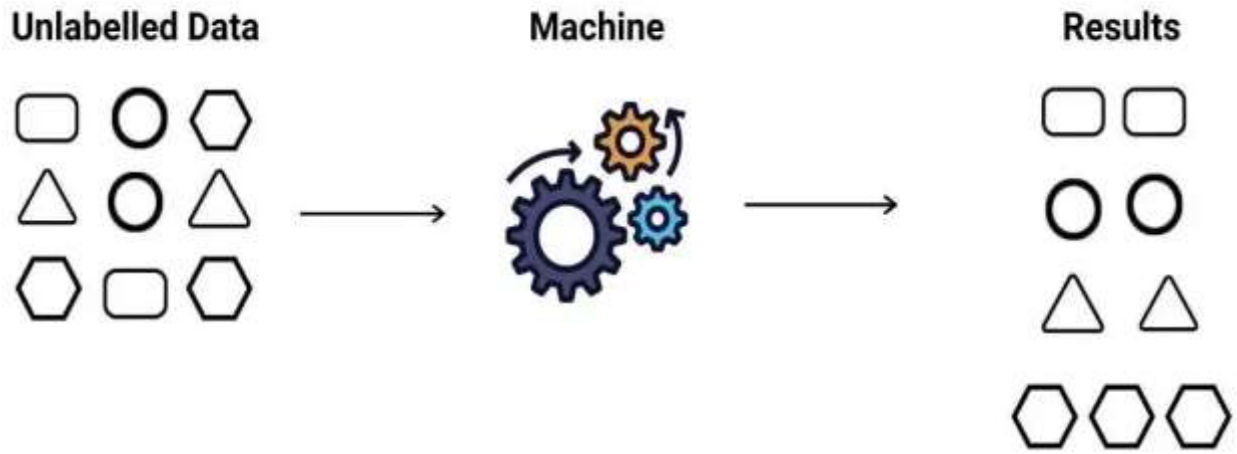

Figure 3: Unsupervised learning model

2.3. Supervised learning

Supervised machine learning algorithms are designed to learn from examples. The name supervised learning also comes from the idea that teaching these types of algorithms is like having a teacher supervise the entire teaching process. When training a learning algorithm with an observer, the training data consists of inputs paired with correct outputs; That is, the data has the correct output label. During training, the algorithm looks for patterns in the data that are related to the desired outputs and learns those patterns. After training, the supervised learning algorithm receives new inputs whose intended output is not known. Based on the previous training data, it determines which label the new inputs are to be classified, or in other words, what is the output. The goal of a supervised learning model is to predict the correct label for new input data.

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 .

In its simplest manifestation, supervised machine learning can take the form of multiple linear regressions, 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, k-nearest neighbors , Hidden Markov Models, and Markov Chain Monte Carlo methods . These techniques are founded on distinct mathematical models and assumptions, each demonstrating excellence in diverse domains.

Among supervised machine learning models, neural networks have garnered immense attention, especially with the evolution of Deep Learning , 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.

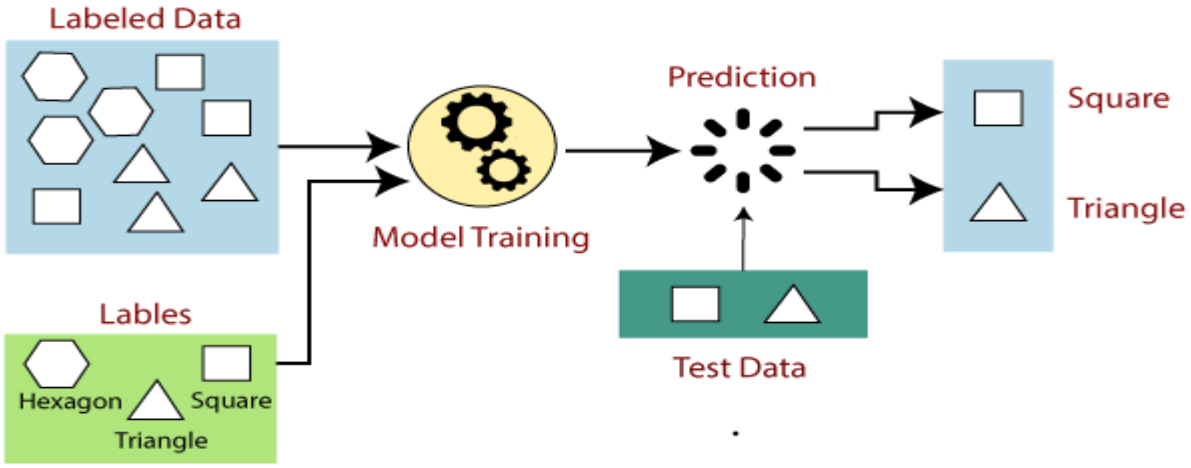

Figure 4: Supervised learning model

2.4. Neural networks and deep learning

Neural networks in deep learning include convolution neural networks, recurrent neural networks, etc. In this article, we will teach neural networks in deep learning and define the types of neural networks that are used in deep learning. Deep learning is a subset of artificial intelligence in which a machine is used instead of a human. First, we must say that the human brain is made up of nerve fibers that are connected to each other and process information. It is based on the inputs we receive and basically our brain behaves like a function that takes inputs and performs operations and delivers the output to us. Deep learning also uses a deep neural network that works like the human brain. Slow and does processing. The more the number of layers and nerves in each hidden layer, the more complex the model becomes, when these neural networks that contain more than three layers of input and output layers are called deep neural networks and their learning is deep learning. It is believed that by means of these deep neural networks, very complex problems in the field of prediction and classification are solved into simple problems. In fact, deep learning is a function that transforms input into output. Deep neural network finds the connection between input and output data. The deepness of the neural network means that these networks are multi-layered. The layers of the neural network are made up of nodes. A node, like the human brain, is a place to perform calculations. In a node, the input data is multiplied by a weight. The more this weight is, the greater the impact of the data,

after that, the sum of the data multiplied by their weight is calculated. Finally, to reach the output, the obtained total passes through an activation function and outputs.

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 . 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 . 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 , as well as complex scientific tasks like protein folding . 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 .

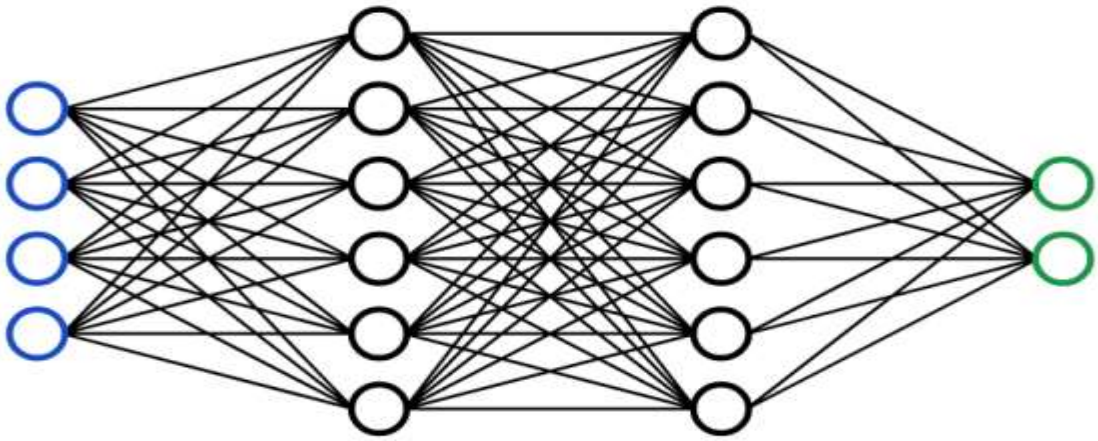

Figure 5: Model of neural networks and deep learning

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 ۱۰.

Table 1: Summary of previous research

	Authors	Method		Authors	Method
1	Chun Chou et al	PBPK	۱	Zhang et al	Deep Learning
2	Monirul et al	MobileNet	۲	Farajzadeh et al	Deep Learning
3	Zhang et al	Machine learning	۳	Ren et al	ANN

4	Anaya-Isaza et al	Cross-Transformer	۴	Ruba et al	Deep Learning
5	Sharma et al	CNN	۵	Ranjbarzadeh et al	CNN
6	Tripathy et al	CNN	۶	Fernando & Toskos	Deep Learning
7	Patil & Kirange	SCNN	۷	Raghuram & Hanumanthu	SDNN
8	Chakrabarty & Mahajan	CNN	۸	Talukder et al	Deep Learning
9	Alemu et al	SVM	۹	Shyamala & Brahmanada	Regression Neural Network
10	Yaqub et al	ALCResNet	۱۰	Rezai	CNN

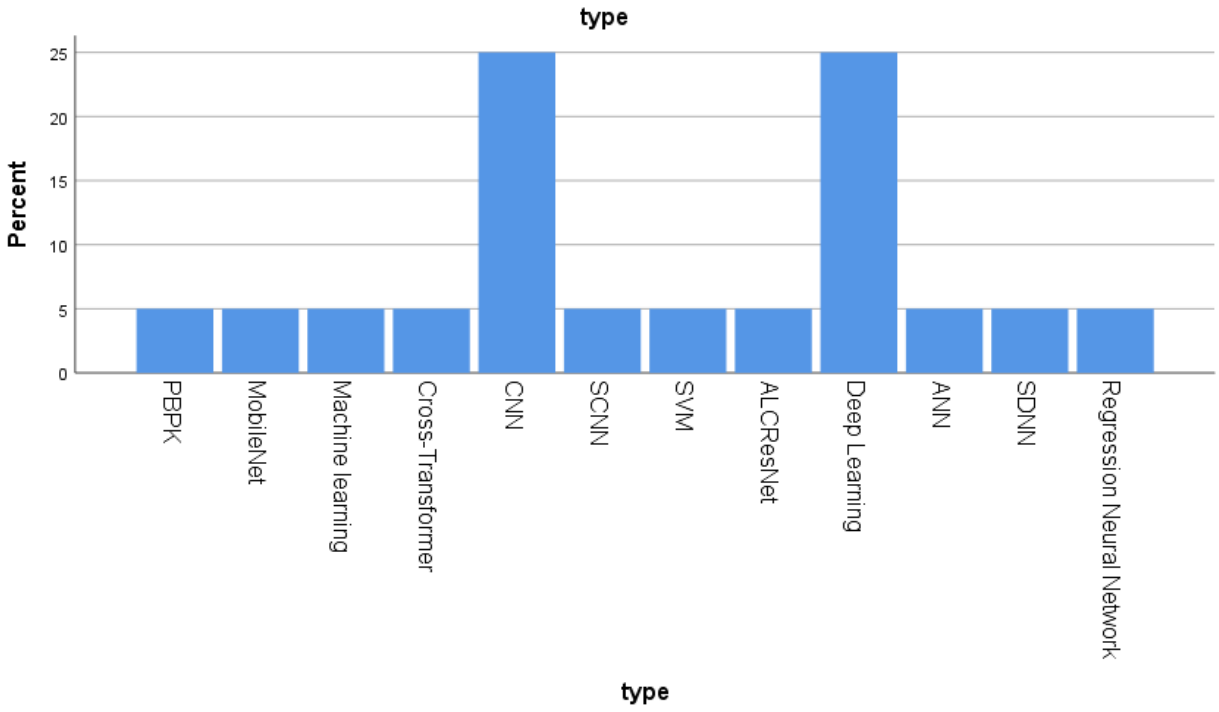

Figure ۶: Frequency of using each method

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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