AI Reloaded: Objectives, Potentials, and Challenges of the Novel Field of Brain-Like Artificial Intelligence

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Abstract

The general objective of Artificial Intelligence (AI) is to make machines – particularly computers – do things that require intelligence when done by humans. In the last 60 years, AI has significantly progressed and today forms an important part of industry and technology. However, despite the many successes, fundamental questions concerning the creation of human-level intelligence in machines still remain open and will probably not be answerable when continuing on the current, mainly mathematic-algorithmically-guided path of AI. With the novel discipline of Brain-Like Artificial Intelligence, one potential way out of this dilemma has been suggested. Brain-Like AI aims at analyzing and deciphering the working mechanisms of the brain and translating this knowledge into implementable AI architectures with the objective to develop in this way more efficient, flexible, and capable technical systems This article aims at giving a review about this young and still heterogeneous and dynamic research field.

Keywords: Brain-Like Artificial Intelligence, Artificial Brains, Human-Level Machine Intelligence

1. Introduction

The research field of Artificial Intelligence (AI) is concerned with making machines – particularly computers – do things that require intelligence when done by humans. In the 60 years of its existence, it has celebrated dramatic successes and equally dramatic failures. Today, AI has become an important and essential part of technology and industry and provides solutions to some of the most complex problems in computer science. Nevertheless, in terms of its original goal – to create true human-level intelligence in machines – Strong AI has not succeeded yet and perhaps never will. Today, AI researchers are able to create computers that can perform jobs that are difficult for persons like logic, algebra problem solving, path planning, or playing chess. However, they are still struggling with developing a computer that is capable of carrying out tasks that are simple to do for humans like perceiving their environment, assessing complex situations, and taking everyday life decisions. Approaches in the past have mainly concentrated on creating intelligence in computational devices by developing programs that exhibit some kind of "behavior" or "skill" that resembles specific facets of human (or animal) behavior or skills. Investigating the structures, information processing principles, and functions in the brain that lead to the emergence of such behavior and skills was so far generally out of scope of AI technology. For this reason, today's computers and AI programs have simply very little in common with actual brains and minds. Unfortunately, if continuing this mainly mathematically-algorithmically oriented path, any major breakthrough in AI is rather improbable. A paradigm shift might be necessary. With the novel research field of *Brain-Like Artificial Intelligence*, one potential way out of this dilemma has been suggested [111, 137]. However, the discipline of Brain-Like Artificial Intelligence is still not broadly recognized and so far a common research community has not established. Researchers influencing this domain are in fact mostly situated on the borders of other research fields. So far, no standard textbooks or overview articles exist concisely defining the field and explaining the objectives, methodologies, difficulties, etc. Those who want to gain insight into this domain have to laboriously gather up and put together information themselves from bits widely scattered through literature. These circumstances of course do not contribute to an acceleration of the developments in this field. To overcome this problem, this article aims to provide a first comprehensive review on this young domain of science. Although it might happen that certain other researchers of this so far disparate and scattered field will disagree on particular points described in this general overview or claim additional material, such a first draft (or chapter) of a "manifesto" for Brain-Like AI can certainly constitute a basis for fruitful discussions and contribute to further development.

The review starts with a brief discussion of the field of Artificial Intelligence in general and of important current sub-disciplines and their flaws in Chapter 2 in order to better understand the backgrounds that led to the emergence of the domain of Brain-Like Artificial Intelligence. Afterwards, Chapters 3 to 8 focus on the description of the field of Brain-Like Artificial Intelligence. Chapter 3 outlines the basic concept and the general aims of Brain-Like AI. Chapter 4 lists examples of conferences, journals, individual researchers, and research groups that have started to promote and support the idea of brain-inspired AI design. In Chapter 5, a demarcation of the current concepts to artificial neural networks – one of the most prominent ancestors of Brain-Like AI – is made. Afterwards, a classification scheme for approaches so far presented is proposed in Chapter 6. Next, current problems, stumbling blocks, and challenges of the field are summarized in Chapter 7. Last but not least, a route for how to overcome these problems in the future is suggested in Chapter 8.

2. The field of artificial intelligence today and relevant sub-disciplines

„Artificial Intelligence (AI) is the science of making machines do things that would require intelligence if done by humans" [83]. The basic claim of AI is that the central property of (human) intelligence can be precisely described and thus simulated by a machine [78]. Over the last 60 years, AI has changed from a computational discipline into a highly interdisciplinary field incorporating many areas [128]. Artificial Intelligence has given rise to optimism [65, 115], but has also suffered severe setbacks [4, 137]. Today, it constitutes an essential part of technology and industry and is providing solutions to some of the most complex problems in computer science [65]. Although there does not seem to exist a formal, generally accepted definition for Artificial Intelligence, various suggestions for specifying the field of AI (or rather particular sub-domains) have been made over the years. John McCarthy, who introduced the term in 1956 [29], defines it as *„the science and engineering of making intelligent machines"* [78]. More recent AI textbooks describe the domain amongst others as *„the study and design of intelligent agents"* [98] where an intelligent agent is a system that *„perceives its environment and takes actions that maximize its chances of success"* [108]. Today, AI research is highly specialized and deeply divided into sub-domains that have little in common with each other and therefore often fail to communicate [79]. Sub-branches have grown up around the work of individual researchers, particular institutions, the solution of specific problems, the application of widely differing tools, and longstanding differences of opinion about by what methodology AI should or can be achieved. In the following, a suggestion for a classification of these approaches into five different groups is given (Section 2.1) followed by a discussion of the strengths and weaknesses of each group (Section 2.2).

2.1. A possible classification of existing approaches into sub-disciplines

Providing a generally accepted taxonomy for classifying existing approaches into sub-disciplines of AI is not an easy task. Due to the heterogeneity of the field and the overall lack of interchange between groups with different ideologies, there seems to exist more confusion than consensus about this topic. Part of the researchers propose a distinction according to either the particular method used (rule-based systems, neural networks, statistics, fuzzy logics, genetic algorithms, ontologies, etc.) or the application (pattern recognition, optimization, planning, theorem proving, machine vision, language processing, reasoning, etc.). However, in practice, this leads to lists of AI classes easily containing several hundred items. If a researcher does not find an appropriate entry for his/her research, he/she is tempted to introduce a new term, which does not really contribute to a resolution of the categorization problem. Therefore, it is suggested here to better distinguish approaches based to their ideology, methodology, and goal. Accordingly, a classification of the five AI sub-disciplines as described below is proposed, including a description of the core essence of each of these domains. The first three sub-disciplines (Applied Artificial Intelligence, Artificial General Intelligence, and Embodied Artificial Intelligence) are the ones that are the most broadly known today. The further two sub-disciplines (Bio-Inspired Artificial Intelligence and Brain-Like Artificial Intelligence) have been less often explicitly mentioned in literature, are however relevant for this article.

When reading these descriptions, one has to be aware that for Artificial Intelligence in general as well as for the existing sub-disciplines, different, partly not complementary definitions can be found in literature for one and the same term. One example of this are the terms Strong AI and Weak AI, which were originally introduced by J. Searle [110] as part of his Chinese room argument to distinguish between two different hypotheses about Artificial Intelligence. According to the Strong AI hypothesis, a suitably designed computer system can actually replicate aspects of human intelligence and thus have a mind. According to the Weak AI hypothesis, a computer system can (just) simulate aspects of human intelligence and thus (only) act as if it had a mind. This initial usage of those terms is fundamentally different from the way they are widely used today in academic AI research and textbooks. Nowadays, these terms are often rather used to distinguish two particular AI sub-domains (see below) instead of two hypotheses about the achievable goal of AI. Furthermore, one has to be aware that boundaries between the different suggested sub-disciplines can in some cases be a bit blurry. Being able to provide a perfect, unambiguous taxonomy in a field like AI is probably an illusion. It can thus happen that a particular approach could theoretically be assigned to more than one sub-discipline. For instance, a neural network approach could principally be regarded as a bio-inspired (maybe even slightly brain-inspired) approach. If the focus is however rather on employing a “pre-fabricated” network type to solve a very particular task (e.g., the classification of metallic parts of different shapes [133]), it should better be considered as a method of Applied AI. Thus, looking at the objectives, methodology, and followed ideology of a research approach is important for achieving the most adequate categorization.

- **Applied Artificial Intelligence:** One potent sub-field of AI, also referred to as mainstream AI by some authors, is Applied Artificial Intelligence [27] (also called Narrow Artificial Intelligence [46] or Weak Artificial Intelligence [17]). Applied AI is concerned with the use of hardware and software to study or accomplish specific tasks of problem solving or reasoning that do not encompass the complete range of human cognitive abilities or are in most cases even completely outside their focus. Applied AI researchers aim at creating programs that demonstrate “intelligence” in a specialized area such as medical diagnosis, chess playing, algebraic calculation, mathematical theorem-proving, automobile-driving, etc.
- **Artificial General Intelligence:** A second sub-domain of AI is Artificial General Intelligence (AGI) [46]. AGI is not a precisely defined term. P. Wang and B. Goertzel [146] report that in contrast to Applied AI, which aims at particular aspects of applications of intelligence, AGI aims at “intelligence” as a whole, having many aspects and being applied in many situations. R. Koene [61] points out that *“some AGI researchers are explicitly pursuing forms of (general) intelligence designed from first principles and without a desire for comparability or compatibility with human intelligence”*. However, he also states that *“many of the underlying objectives that drive the search for AGI also involve an interest in anthropomorphic interpretations of intelligent behavior”*. In the proceedings of the third International Conference on Artificial General Intelligence in 2010, AGI is described as the research field focusing on the original and ultimate goal of AI – to create broad human-like and trans-human intelligence by exploring all available paths, including theoretical and experimental computer science, cognitive science, neuroscience, and innovative interdisciplinary methodologies [12]. Some researchers place the term AGI today more or

less on a level with the term Strong Artificial Intelligence [27]. In contrast to its original use, Strong AI now refers to the design of machines of human intelligence level, i.e., machines that can successfully perform any intellectual task a human being can do [65]. C. Pennachin and B. Goertzel [94] point out that the term Artificial General Intelligence (AGI) was introduced in order to avoid the connotations "human-level" or "human-like"' of the term Strong AI, which were widely used before, and to further allow the inclusion of non-human models.

- **Embodied Artificial Intelligence:** A third important sub-discipline of AI is Embodied Artificial Intelligence [97] (also called Embodied Intelligence [18], New Artificial Intelligence [87], Behavior-Based Artificial Intelligence [76], or Nouvelle Artificial Intelligence [96]). The goal of Embodied Artificial Intelligence is to study *"how intelligence emerges as a result of sensorimotor activity, constrained by the physical body and mental developmental program"* [127]. Accordingly, the field of embodied intelligence is strongly connected to the design of "intelligent" agents that perceive their environment and take actions that maximize their chances of success [108].
- **Bio-Inspired Artificial Intelligence:** Another sub-discipline of AI is the field of Bio-Inspired Artificial Intelligence [39] (also mentioned in correlation with Biologically-Inspired Artificial Intelligence [25], Naturally-Inspired Artificial Intelligence [13], Bionics [132], and Artificial Life [14]). Bio-Inspired Artificial Intelligence focuses on the design of intelligent machines by taking inspiration from biology. J. Chappell et al. [24] point out that this includes *"(1) attempts to mimic details of the morphology and behavior of humans or other animals; (2) attempts to apply theories about how neural or evolutionary mechanisms work, to solve engineering problems; (3) applying techniques inspired by social behaviors of organisms, including swarming, flocking, use of pheromone trails, etc.; (4) attempts to understand the problems solved by biological evolution in order to clarify goals and requirements for AI/robotics."*
- **Brain-Like Artificial Intelligence:** A further emerging sub-domain of AI holding great promises and being subject of this article is the field of Brain-Like Artificial Intelligence [41, 111] (also called Brain-Inspired Artificial Intelligence [137]). Brain-Like Artificial Intelligence – a term that is currently being established [111] – is concerned with investigating how the human (or animal) brain is structured and how it functions with the aim to emulate these concepts for the design of more efficient, effective, and "intelligent" technical systems [137, 73].

2.2. Weak points of current sub-disciplines

In the approximately 60 years since its development and implementation, research in Artificial Intelligence has produced many useful outputs in terms of solved technical problems and has also contributed insights to our understanding of the "nature of intelligence". Nevertheless, the overall challenge of developing "truly intelligent machines" applicable for all kinds of tasks that can be solved by humans is enormous and much remains to be done to overcome it. Different sub-disciplines of AI have targeted this challenge from different perspectives. Brilliant researchers can be found in each of them. Nevertheless, each field today still shows certain "intrinsic" weak points. An attempt to identify and describe them is made in the following.

Applied Artificial Intelligence

Although there exist initiatives to encourage people to focus on the advancement of the scientific understanding of cognitive systems[1], researchers today choose to focus for the most part on Applied AI [94], i.e., specific sub-problems such as data mining, computer vision, logistics, speech recognition, medical diagnostics, banking software, industrial robotics, search engines, etc.,

[1] http://www.socsci.ru.nl/CogSys2/PDFs/Cogsys2_Opening_by_Colette_Maloney.pdf

where they can produce commercial applications and verifiable results [90, 108]. Applied AI can therefore be considered as AI mainstream research direction. Some of the methods and programs developed in this context are extremely successful in what they do [94]. Some AI researchers today still hope that more general purpose AI systems can emerge by combining the programs that solve various sub-problems using an integrated subsumption architecture, agent architecture, or cognitive architecture [44, 86]. However, the success of achieving a general level of intelligence by such "superposition approaches" is heavily doubted by other AI researchers. In an interview in Hal's Legacy in 2000, M. Minsky, one of the pioneers and co-founders of AI, pointed out that *"we really haven't progressed too far toward a truly intelligent machine. We have collections of dumb specialists in small domains; the true majesty of general intelligence still awaits our attack. We have got to get back to the deepest questions of AI and general intelligence and quit wasting time on little projects that don't contribute to the main goal."* [45]

Artificial General Intelligence

Excessive optimism in the 1950s and 1960s concerning Artificial General Intelligence – although at this time this name was not used – has given way to the recognition of the extreme difficulty of creating human-level intelligence, which is today considered as the possibly hardest problem that science has ever undertaken. Thus, in the following decades, most AI researchers have devoted little attention to Artificial General Intelligence. Nevertheless, today, a small number of scientists are active in AGI research. The research is extremely diverse and frequently pioneering in nature. Estimates of the time needed before a truly flexible AGI system could be built, if at all, vary from a decade to over a century [94]. R. Kurzweil and colleagues point out that a timeframe between 2015 and 2056 is plausible [65]. However, many AI researchers of other sub-disciplines are not at all convinced that progress will be that fast. Critics doubt whether research in the next decades will even produce a system with the overall intellectual ability of an ant [27].

Embodied Artificial Intelligence

While Applied AI and Artificial General Intelligence have been centered round the idea of the computational representation of the world, the approach of Embodied AI is centered around action in the world. Embodied Intelligence suggests that the basic assumption of traditional AI, according to which cognition is equal to computation, is not adequate and needs to be reconsidered. When the digital computer was invented, many felt that the core and essence of thinking and intelligence had been found. Computers were considered "electronic brains" in those days and the human mind was viewed as a computer [96]. In the 1980s and 1990s, a subset of researchers from Artificial Intelligence, psychology, cognitive science, and brain science eventually realized that the idea of computers as intelligent machines, at least in the form they exist today, was misguided. They concluded that the brain does not run "programs" and has not evolved to perform mathematical proofs[2] but to control behavior that ensures the organism's survival in the real world [96]. Accordingly, they further concluded that intelligence needs a body equipped with sensors and actuators and an environment on which to act. Based on this claim, a new sub-discipline of AI evolved: the field of Embodied Artificial Intelligence [18]. Embodied Intelligence has moved its focus away from computers and towards more interactive systems such as robots or ubiquitous environments equipped with many sensors and actuators. It focuses not necessarily on human intelligence but rather on non-human biological systems such as insects [97]. Important research areas in Embodied AI today include walking, locomotion, low-level sensory-motor intelligence, orientation behavior, path-finding, elementary behaviors such as following and obstacle avoidance, etc. [97].

[2] In this context it should be mentioned that other researchers partly disagree, as certain animals and particularly humans need cognitive capabilities that allow for planning (acting-as-if), for instance, in order to cope with dangerous situations where a solution cannot be worked out by trial and error as this would most likely result in getting injured or killed [28,125].

Although usually not directly related to each other in scientific literature [92], Embodied Artificial Intelligence seems to have much in common with the domain of Cybernetics [57], which already emerged approximately a decade before the field of AI was founded [149]. Cybernetics was particularly interested in the question of how *"animals and humans maintained equilibrium within, and responded appropriately to, their ever-changing environment"* [70].

Today, the field of Embodied Artificial Intelligence is still highly diverse and far from being theoretically stable [97]. Interestingly, many researchers of Embodied Intelligence do not refer to themselves as working in Artificial Intelligence but rather in robotics, engineering of adaptive systems, artificial life, adaptive locomotion, bio-inspired systems, and neuroinformatics [97]. In Embodied AI, the identification of the fact that natural intelligent systems are all biological and have to perceive and interact with their environment was without a doubt an important step. However, unfortunately, this approach offered new pitfalls. One essential criticism of Embodied AI is that the slogans of embodiment encouraged researchers to focus exclusively on "on-line" interaction of robots with the environment (see for example [101]) without "reflecting" about their activities (e.g., to consider what they did before, why they did it, what would have happened if they had not done it, whether they should try something different next time, etc.). R. Pfeifer and F. Iida [97] point out that *"to date, most robots are specialized, either for walking or other kinds of locomotion purposes, or for sensory-motor manipulation, but rarely are they skilled at performing a wide spectrum of tasks. One of the fundamental unresolved problems has been and still is how thinking emerges from an embodied system. Proactively speaking, the central issue could be captured by the question: How does walking relate to thinking?"* Thus, what happened in the field of Embodied AI was that most researchers failed to consider "disconnected" cognition not directly involving sensorimotor coordination as much as researchers in earlier AI failed to consider "connected" (online) cognition, though there was more justification for the omissions in the early days of AI due to still inadequate technology. In this context, A. Sloman [124] mentions that *"the tautology that a robot that acts and perceives in the world must be embodied is often combined with false premises, such as the premise that a particular type of body is a requirement for intelligence, or for human intelligence, or the premise that all cognition is concerned with sensorimotor interactions, or the premises that all cognition is implemented in a dynamical system closely coupled with sensors and effectors"*. He further criticizes that *"robots so far produced by „nouvelle AI" are pre-constructed and typically move around rather pointlessly (possibly doing something useful as a side-effect), or achieve arbitrary goals imposed from outside, as opposed to doing what is required to grow, maintain, or reproduce themselves"*. J. Starzyk [128] points out that *"Embodied Intelligence revived the field of autonomous robots, but as robotics thrived, research on Embodied Intelligence started to concentrate on the commercial aspects of robots with a lot of effort spent on embodiment and a little on intelligence. Researchers today concentrate on advancements of robotic technology like building artificial skin and muscles. While this might be relevant for the development of robots, it diverts attention from developing intelligence. Furthermore, currently, process efficiency dominates over generality. It is more cost efficient and cheaper to design a robot for a specific task than one that can perform various tasks, and most certainly even more than one that can actually make its own decision"*.

Bio-Inspired Artificial Intelligence

Parallel to the emergence of Embodied Intelligence, more attention also started to be directed towards the derivation of biological concepts [97]. While Artificial Intelligence has traditionally focused on the computational reproduction of the behavior and abilities of humans, Bio-Inspired AI takes inspirations from a wider range of biological structures that show the capability of adaptation and autonomous self-organization. N. Forbes [38] describes the focus of the field to be on *"the use of biology in algorithm construction, the study of how biological systems communicate and process information, and the development of information processing systems that use biological materials, are based on biological models, or both"*. As outlined in [39, 75, 11], Bio-Inspired AI envisions amongst others evolutionary computation, evolutionary electronics, biologically inspired hardware, bioelectronics, amorphous computing, artificial immune systems, genetic algorithms, DNA computation, cellular automata, biomolecular self-assembly, artificial neural networks, biorobotics, and swarm intelligence. In the book *"Bio-Inspired Artificial Intelligence – Theories, Methods, and Technologies"*, D. Charles et al. [25] categorize Biologically-Inspired approaches to AI into 7 groups: evolutionary systems, cellular systems, neural systems, developmental systems, immune systems, behavioral systems, and collective systems. Like Embodied AI, Bio-Inspired AI also has some common roots with the field of Cybernetics, which is interested in human and animal nervous systems [70]. However, the central aim of Cybernetics is the understanding with less emphasis on the construction of useful artifacts. Without doubt, Bio-Inspired AI and bio-inspired technology have great potential. However, approaches suggested in this field are of great diversity, which makes it difficult to provide an analysis of the strengths and flaws of this domain with general validity. While some approaches like artificial neural networks and genetic algorithms are already well established methods that find application in various areas, many others are still on the level of very basic research and concept clarification. Bio-Inspired AI is not yet widely considered as an own, separate research field, but rather it summarizes biologically-inspired approaches introduced in diverse other disciplines. In general, the term "bio-inspired" implies that inspiration for technical development is taken from nature. However, the level of abstraction at which nature serves as archetype varies greatly. Part of the approaches currently consider and investigate information processing and computational principles occurring in nature while others analyze biological organisms on a behavioral level or take nature more as a metaphor than as a model [38]. In the latter context, B. Sendhoff et al. [111] criticize that so far, the contribution of so called "Bio-Inspired" AI approaches to a better understanding of "biological intelligence" and "brain intelligence" has been very limited. Similar as in classical AI, there exist a number of approaches that have resulted from a symbiotic cooperation between engineers, computer scientists, and researchers from life sciences. However, a significant number of models are still developed by researchers from the technical science discipline only. A. Schierwagen [109] comments that in practice, this has sometimes led to so-called bio-inspired technologies that take advantages of fancy biological names as selling arguments without an in-depth exploitation of biological principles.

Artificial Intelligence as a Whole

In summary, it can be concluded that throughout its history, Artificial Intelligence has always been a topic of much controversy [29, 90]. Taking inventory today, Artificial Intelligence can achieve good solutions that can compete with or exceed human (or at least higher developed animal) cognitive abilities and skills for problems that are sufficiently well structured and whose complexity can be controlled. Today's AI systems particularly outperform humans in jobs that are of an "abstract nature" like logic, solving puzzles and algebra problems, path planning, playing chess, etc. and that can be well described in a mathematic or algorithmic form and thus be relatively easily implemented computationally (see also [97]). Certain problems have these characteristics. However, natural environments do not [111]. AI researchers have so far struggled to develop computational systems that are capable of carrying out tasks that are simple and "natural" for humans, e.g., perception in the real world, object manipulation, sensory-motor coordination, locomotion, common sense, evaluating complex situations, making decisions in real world situations, everyday natural language, etc. [96, 137]. J. Starzyk [128] criticizes that Artificial Intelligence often applies the principle of chip design to create a system with no intelligence and call it intelligent as long as it does its job. During its history, Artificial Intelligence challenges have experienced a revival in various disciplines related to AI, e.g., computational intelligence [98], cognitive automation [129], cognitive computation [55], and cognitive robotics [26]. However, the basic aims and difficulties have remained mainly intact.

Despite the many successes of Artificial Intelligence, fundamental problems of intelligence are still unanswered today [128]. As B. Sendhoff et al. [111, 112] point out: *"Superior functionality* *in a single problem domain can often already be achieved by specialized technological systems (thinking about a simple calculator or a chess program), however, no technological system can robustly cope with the plethora of tasks encountered by any* (higher developed) *animal during its life time. We have to acknowledge that in spite of its tremendous advances in areas like neural networks, computational and artificial intelligence, and fuzzy systems, existing approaches are still not able to mimic even for instance the lower-level sensory capabilities of humans or animals."*

Thus, the open question remains: *How to continue on the path to machine intelligence for the problem domains that cannot yet be handled with existing approaches?* An emerging path that – if followed wisely – could hold a solution to this question is the field of *Brain-Like Artificial Intelligence*.

3. The basic concept and aims of Brain-Like Artificial Intelligence

3.1. Basic concept

As outlined in Section 2.2, Artificial Intelligence today mainly provides methods and tools to automate specific, well-structured tasks that take place in environments of limited complexity. For tasks that show these characteristics, technical systems can compete with or even surpass human performance. However, there does not currently exist a technical system that can even come close to competing with the overall capacity and the capabilities of the human mind. The same holds true for perceptual, motor control, and other cognitive abilities of higher developed animals. In order to substantially progress further a paradigm shift might be necessary in this field. With Brain-Like AI, a potential way out of the current AI dilemma has been proposed. Its basic idea is highly intuitive [35, 95, 99, 135]: *use the brain as archetype for AI model development!* However – considering the last 60 years of AI history – it is quite clear that it has so far not been that easy to implement this idea properly (see also Chapter 7).

One difficulty with current approaches in Brain-Like Artificial Intelligence is, as it can also be observed in other sub-disciplines of AI, that different researchers have partly divergent opinions on what Brain-Like Artificial Intelligence actually is and how it should be done (see also Chapter 7). In the book *Creating Brain-Like Intelligence: From Basic Principles to Complex Intelligent Systems*, B. Sendhoff et al. [111] point out: *"As the name suggests, we would like to achieve intelligence as demonstrated by brains preferably those of highly evolved creatures."* Although part of the contributions presented in this book actually aim at investigating and emulating the structures, information processing principles, and functioning of the brain that lead to the emergence of certain skills and abilities, it is left open if an analogy to the brain is sufficient in terms of externally emitted functions or if it should also be in terms of internal processes and principles. However, if limiting the similarity to emitted functions, no clear demarcation line to the other fields of AI discussed in Section 2 – particularly to AGI – can be drawn. Brain-Like Artificial Intelligence as understood in this article therefore refers to both similarity in internal brain processes and principles and their emitted function. While principally the brain of different higher developed organisms could be analyzed for this purpose (see also Section 6.1), the focus is on the human brain in this article. Accordingly, the "basic dogma" of Brain-Like Artificial Intelligence as used here is the following:

"Basic Dogma" of Brain-Like Artificial Intelligence as Used Here
It is well appreciated that the human brain is the most sophisticated, powerful, efficient, effective, flexible and intelligent information processing system known. Therefore, the functioning of the human brain, its structural organization, and information processing principles should be used as archetype for designing artificial intelligent systems instead of just emulating its behavior in a black box manner. To achieve this, approaches should not build on work from engineers only but on a close cooperation between engineers and brain scientists.

Acknowledging the simplicity, clarity, and intuitive logic of this basic dogma, the question arises why such a brain-like approach to AI has not already been followed more intensively from the very beginning of the field of AI. One main reason for this is that 60 years ago, when the domain of AI started to evolve, the available body of knowledge about the functioning of the brain was still very limited. Apart from simple nerve cell models, the brain could merely be considered as a black box system of which only the external behavior could be observed and studied. The development of new measuring and imaging techniques in the last decades has shed new light on the internal structures, information processing principles, and functioning of the brain. In this context, B. Goertzel [45] states: *"Prior to the last few decades, the traditional disciplines of psychology and neuroscience offered extremely little to AI designers. Since the emergence of cognitive science and cognitive neuroscience, things have gotten a little better."* It might now be time to start using and extending this acquired knowledge by translating it to functioning and technically implementable models.

3.2. Basic aims

In simple words, the research field of Brain-Like AI is concerned with the development and implementation of concepts and models of the human (or animal) brain and their application in various kinds of technical systems and domains. The motivation for research in Brain-Like AI is twofold and outlined in the following [41, 48, 99]:

- On the one hand, these models and their implementation shall in the future lead to better information processing, computation, and automation systems. Domains which are eagerly waiting for such novel "intelligent" approaches in order to deal with their upcoming needs are, amongst others, the field of machine perception [130, 138], sensor fusion [135], ambient intelligence [19], interactive systems [20, 140], smart buildings [67, 136, 139], automation [143], robotics [22, 32, 33], agent technologies [68], information processing [50, 131], computation [6, 142], and web intelligence [151].
- On the other hand, the models shall contribute to a better understanding of the human (or animal) brain. When trying to technically implement models of the brain, unknown points cannot just be left open without even mentioning them as the developed machine has to be able to perform certain functions. Therefore, this emulation process is an important means to detect weak points and inconsistencies in current brain theories and to contribute to the development of new brain theories [82, 138, 141, 144].

Of course, each researcher will place their particular focus in terms of these two basic motivations. While some concentrate on topics of the first point, others may emphasize the second.

4. Support from the scientific community

Although still being a heterogeneous and emerging discipline, the principal idea of brain-inspired approaches to solutions in AI is today well supported by numerous researchers. N. Zhoung [151] points out that *"AI research has not produced major breakthrough recently due to a lack of understanding of human brains and natural intelligence."* He predicts that the next major advancements in AI will most likely result *"by an in-depth understanding of human intelligence and its application in the design and implementation of systems with human-level intelligence"*. M. Minsky suggests that findings about how natural intelligence (particularly the brain) works have to be the basis for developing concepts for technical approaches trying to achieve intelligence [134]. J. Kirchmar and G. Edelman [63] state that *"the analogy to the natural brain must be taken serious"* [112]. C. Pennachin and B. Goertzel [94] comment that *"one almost sure way to create Artificial General Intelligence would be to exactly copy the human brain"*. C. Goerick [42] discusses: *"We would like to create brain-like intelligent systems, hence we have to understand how the brain works. The artifacts we are creating should show what we have understood from the brain so far,* *and should help formulating the next questions aiming for further understanding the brain."* R. Koene [61] indicates that *"the brain's implementation is not necessarily the best one according to criteria used to measure performance at solving a particular problem, but at least it is an existing implementation, and we have some idea of the specifications that it meets"*. D. Dietrich and his team emphasize that one way to solve the dilemma of AI and automation in general is the application of bionic approaches, particularly of approaches considering the human brain and mind. They recommend a close cooperation between engineers and brain scientists for this purpose [21, 35, 68, 91, 100, 104, 134, 150]. J. Hawkins [51] states that *"brains are totally unlike the relatively simple structures of even the most complex computer chip"* and that therefore *"the way we build computers today won't take us down the path to create truly intelligent machines."* S. Potter [99] points out that *"yet, little attention in the AI field has been directed toward actual brains."* He illustrates that *"the human brain is the best example of intelligence known, with unsurpassed ability for complex, real-time interaction with a dynamic world"* and concludes that *"if AI were to become less artificial, more brain-like, it might come closer to accomplishing the feats routinely carried out by natural intelligence*." S. Amari [6] indicates that *"the more is known about the functionality of the brain the more intelligent the information systems will become"*. B. Goertzel [45] points out that *"we have a great deal of respect for the fact that the human brain/mind actually exists and functions, so it would be foolish not to learn from it all that we can."*

Within the last few years, the first conferences and workshops promoting the topic of Brain-Like AI have taken place, e.g., the *Engineering-Neuro-Psychoanalysis Forum* (2007)[3], the *Brain-Inspired Cognitive Systems Conference* (2004–2012)[4], the *Conference on Brain-Inspired Information Technology* (2006)[5], the *International Symposium on Creating Brain-Like Intelligence* (2007)[6], the *International Conference on Brain Informatics* (2009–2012)[7], the *AAAI Spring Symposium* (2006)[8] with the title *Between a Rock and a Hard Place: Cognitive Science Principles Meet AI-Hard Problems*, and the *International Conference on Artificial Neural Networks* (2011)[9] with focus on *Machine Learning re-inspired by Brain and Cognition*. Other conferences have dedicated tracks and special sessions to this topic, e.g., the *INDIN* (2008–2010)[10] on *Cognitive and Computational Intelligence in Industrial Informatics*, the *HIS* (2010) on *Modeling the Mind*[11], and the *Africon* (2011)[12] on *Challenges in Autonomic Systems looking for New Bionic Approaches for Modeling the Mind*.

Similarly, some pioneer journals have started to deal with topics of Brain-Like AI like the journal of *Broad Research on Artificial Intelligence and Neuroscience*[13] or the special issue on *Brain-Inspired Cognitive Agents* of the *ACM Transactions on Intelligent Systems and Technology*[14].

Moreover, the first books have been published promoting the topic of "brain-inspiredness". Among these are the books *Simulating the Mind: A Technical Neuropsychoanalytical Approach* [35], *Creating Brain-Like Intelligence: From Basic Principles to Complex Intelligent Systems* [111], and *Brain-Like Computing and Intelligent Information Systems* [6].

[3] http://www.indin2007.org/enf/index.php
[4] http://www.conscious-robots.com/en/publications/conferences/bics-2010.-brain-inspired-cognitive-systems-confe.html
[5] http://www.elsevier.com/wps/find/bookdescription.authors/712521/description
[6] http://wiredshelf.com/book/creating-brain-like-intelligence-276694
[7] http://wi-consortium.org/conferences/amtbi11/amtbi.php?conf=bi\&here=cfpart
[8] http://www.aaai.org/Press/Reports/Symposia/Spring/ss-06-02.php
[9] http://www.aaai.org/Symposia/Fall/fss08symposia.php\#fs04
[10] http://indin2010.ist.osaka-u.ac.jp/
[11] http://hsi.wsiz.rzeszow.pl/
[12] http://www.africon2011.co.za/
[13] http://www.edusoft.ro/brain/index.php/brain
[14] http://tist.acm.org/CFPs/TIST-SI-BICA-10.pdf

5. Artificial neural networks – the ancestors of Brain-like AI?

When claiming that Brain-Like Artificial Intelligence is a novel and recent research field, one question that will most certainly pop up is: "Is the concept really that new?" The next question that is most likely to follow is: "What about artificial neural networks?" These are justified questions, which will be considered in more detail in the following.

In principle, the drive to study and emulate the functions of the (human) brain might date back thousands of years. However, only with the development of modern day electronics have attempts to emulate the brain and thinking processes become more tangible. In the 1940s, the area of neural network research began to emerge [52, 80]. Since then, artificial neural network (ANN) research has gone through various highs and lows. Today, artificial neural networks are used for pattern recognition, classification, and prediction. Without doubt, ANNs are useful tools and have brought solutions to various problems that are difficult to solve with conventional computers. However, they have yet failed to produce any kind of behavior that could be considered truly intelligent. Several researchers, for instance H. De Garis [31], claimed that this is due to the fact that current networks were just too small in terms of number of used neurons. However, this explanation is most likely insufficient. I. Aleksander [3] indicates: *"The point is that these puzzles are not puzzles because our neural models are not large enough."* Although ANNs have often been viewed as simplified models of neural processing in the brain, today their relation to biological brain architectures is questionable. In fact, artificial neural networks do contain some neuron-like attributes (connection strengths, inhibition/excitation, etc.) but they overlook many other factors, which may be significant to the brain's functioning [103]. J. Hawkins argues that artificial neural network research ignores essential properties of the (human) cortex and instead prefers to focus on simple models that have been successful at solving simple problems [51]. More specifically, up to today, artificial neural networks have mainly been an attempt to emulate processing aspects of individual biological neurons, not of whole neural brain networks and not of learning principles in such biological networks. Unlike brains that seem to have already a great deal of organization present even during fetal development, ANNs generally start from a jumbled, randomized set of connection strengths [103]. The methods for achieving networking through learning in ANNs are based mainly on mathematical models, not on biological ones.

Accordingly, the question to what extent ANNs are actually brain-inspired can be answered as follows. Artificial neural networks, as they exist today, are systems that are loosely patterned on the nervous system. Their basic processing elements can be considered to be brain-inspired (or better neuron-inspired) and the principal idea to put them together to form networks. However, the rest of the framework, i.e., the way how artificial neurons are structured into networks, how their interconnections are determined through learning processes, etc. is based on mere mathematical assumptions. Therefore, it is suggested here that artificial neural networks should rather be classified as an approach of Bio-Inspired AI or even Applied AI than one of Brain-Like AI. Without question, the initial idea behind ANNs is brilliant and it is astonishing how many tasks can today be solved with them. Unfortunately, these promising results in some areas were probably also the reason that have led a number of researchers to come to the inappropriate conclusion that ANNs as they exist today have much in common with brains. In fact, their success has to be mainly attributed to the mathematical theory behind them and not to biological similarities with the brain. Nevertheless, it is not impossible that in the future, further developments in this field based on novel and extended insights from brain research will lead to neural network structures that are actually worthy to be called "brain-like".

6. Possible classifications of Brain-like AI approaches

As outlined before, the principal idea behind Brain-Like Artificial Intelligence has existed for several decades. However, so far, many stumbling blocks and detours had to be taken concerning its implementation. Thus, Brain-Inspired Artificial Intelligence can still be considered a quite novel, dynamic, and heterogeneous field. Different researchers have different opinions regarding by what means and how closely one needs to simulate the brain in order to achieve brain-like behavior [73].

On the one extreme, there are AI approaches that are based purely on abstract mathematical theories of intelligence and do not draw any mapping between natural and artificial cognition at any level. Such approaches, which rest on the assumption of vast levels of computing power greater than anything that will be physically possible in a foreseeable future, have clearly nothing to do with Brain-Inspired Artificial Intelligence as described and defined in this article.

On the other extreme, there are claims, e.g., by R. Kurzweil [64], that the most effective path to Strong AI is to reverse-engineer the human brain to a level as precise as necessary to replicate its function. In practice, this has led to "brain simulations" aiming at a level of precision as detailed as the cellular level – e.g., in the Blue Brain project [77] – or even the molecular level – as in the Cajal Blue Brain project[15].

In sum, regardless of the level of detail of simulation, most approaches suggested so far should be considered as rather loosely brain-like models [41]. Looking at the great variety of existing approaches, finding a good classification scheme for them is not an easy task and category boundaries generally remain vague. Nevertheless, in the following sub-sections, several possible ways for a classification are suggested.

6.1. Biological organism used as blueprint

Traditionally, Artificial Intelligence has focused its attention mainly on the cognitive abilities of humans. The roots for this go back as far as to R. Descartes who stated that only humans are capable of thought. He considered animal behavior as a series of unthinking mechanical responses to stimuli that originate from the animal's internal or external environment [59]. In contrast, many researchers today disagree with this view – at least for higher developed animals. For instance H. Terrace [15] claims that *"animals do think but cannot master language"*. A. Sloman goes even further and attributes animals with some kind of mathematical competences. Specifically, his research interests are related to the biological basis of mathematical competence in humans and creative problem solving in other animals [126]. S. Kak [59] points out that *"as other animals learn concepts nonverbally, it is hard for humans, as verbal animals, to determine their concepts"*.

Based on these facts, Brain-Like Artificial Intelligence aiming at the emulation of brain functions cannot only take inspiration from the human brain but principally also from brain architectures of all kinds of higher developed animals. Thus, the biological species which is taken as inspiration for the blueprint of a brain-like architecture constitutes one possible way of classification. Prominent species for such brain and behavior models have so far ranged from elephants, cats, cheetahs, deer, primates, and squirrels over crows, pigeons, and parrots to octopuses and insects. Nevertheless, as A. Sloman pointed out in a private discussion with him, one has to be aware that no matter which organism's brain we take as archetype, we cannot avoid explicitly or implicitly focusing on human brains, or at least their competences. After all, we have (at least initially) to use human ways of thinking when we ask what other organisms can and cannot do.

6.2. Bottom-up versus top-down design

Another possibility of categorization is – similar as also in mainstream AI – a division into bottom-up (neural) models and top-down (symbolic) models [27]. Generally, in top-down AI, cognition is treated as a high-level phenomenon that is independent of the low-level details of the implementing mechanism. Researchers in bottom-up AI take an opposite approach and simulate networks of neurons. They then investigate what aspects of cognition can be recreated in these networks.

[15] http://cajalbbp.cesvima.upm.es/

6.3. Involved discipline of brain science

A further method of classification would be the discipline of brain science that served as the inspiration for the technical model. Disciplines today involved in this task range from neuroscience over psychology and pedagogics to psychoanalysis. While neuroscience can be considered as a "bottom-level" approach, the further disciplines target the problem of creating Artificial Intelligence from a "top-level" perspective. Furthermore, in the last decades, disciplines started to emerge, which aim at investigating both top and bottom-level aspects of cognition and particularly their correlations. Amongst these are neuro-psychology, neuro-psychoanalysis, and cognitive neuroscience.

Although the methodology of classification based on the underlying brain theory would make sense, it does not seem to have yet found its way into scientific literature. One problem with this kind of classification might certainly be that today, the content and borders of each of these disciplines of brain sciences and cognitive sciences are not clearly defined. Each discipline is again split into further sub-disciplines, which show partial overlap but partial contradiction with other sub-areas. None of the disciplines can so far provide a satisfactory explanation for how the brain works and accordingly cannot yet give a detailed prescription for the construction of truly "intelligent" systems [45] (see also Chapter 7).

6.4. Emulated brain function

Another possible way of classification can be done according to the brain function that is emulated. This can range from vision, audition, multimodal perception, and motor control over language processing, decision-making, reasoning, and planning, to emotions, learning, and consciousness. In sum, the effort spent so far in truly brain-like approaches to these challenges is still quite limited. The field which has probably received the most attention is computer and machine vision, particularly for the lower processing levels. Interestingly, also in brain sciences, the lower levels of vision are one of the best explored systems of the brain [Nishimoto2011]. In this work, the focus is particularly on the development and implementation of models for multimodal perception, "emotional" situation assessment, and decision-making and their interplay.

6.5. Large-scale brain simulations versus (brain-inspired) cognitive architectures

A methodology related to the bottom-up and top-down categorization of Section 6.2 but perhaps more contemporary for a distinction of brain-inspired approaches is suggested by H. Garis et al. [41] and B. Goertzel et al. [48]. This taxonomy will be described more in detail in the following. The authors distinguish between *large-scale brain simulations* and *(biologically inspired) cognitive architectures*[16]. In the following, a description of these two classes of approaches is given including a number of examples of so far proposed models. For this purpose, the review articles [48] and [41] will serve as the main references. This description does not at this point include a judgment to which extent the individual mentioned models are actually brain-inspired. A critical reflection about the usage of the term "brain-inspired" and the problems coming along with it is given in Chapter 7.

Large-scale brain simulations

Large-scale brain simulations describe systems that attempt to simulate in software the structure and dynamics of particular subsystems of the brain. When looking at existing approaches to large-scale brain simulations, it becomes clear that the scope of interpretation of the notion "brain simulation" is broad. Different researches are approaching this task with very different objectives in mind. H. Garis et al. [41] distinguish between five groups ordering them according to decreasing neurobiological fidelity:

[16] The term "biologically inspired" as used by H. Garis and B. Goertzel mainly refers to architectures inspired by the brain and shall therefore be described under the term brain-inspired cognitive architectures in the following.

1. Models, which can actually be connected to parts of the human brain or body and that can serve the same role as the brain system they emulate. An example is Boahen's artificial retina [16].
2. Precise functional simulations of subsystems of the brain, their internal dynamics, and their mapping of inputs to outputs that explain exactly what the brain sub-system does to control the organism.
3. Models, which quantitatively simulate the generic behavior and internal dynamics of certain brain sub-systems, however, without precisely functionally simulating these sub-systems. The best known examples of this type are Markram's cortical models promoted within the Blue Brain Project [77] and its continuation, the Human Brain Project[17]. Furthermore, such approaches are amongst others targeted by Izhikevich's simulations [56] and Edelman's brain-based devices [62].
4. Models, which quantitatively simulate subsystems of the brain or whole brains at a high level, not including a simulation of the particular details of dynamics or inputs/outputs. Such approaches have the aim to explore some of the overall properties of the given system. Examples are Just's CAPS work [122] or Horwitz's cognitive simulations [54].
5. Models, which demonstrate the capacity of hardware to simulate large neural models. These models are based on particular classes of equations. However, there is no claim about the match of the models with empirical neuroscience data. Examples are Boahen's Neurogrid work [16], Modha's cat brain simulation [7], or S. Furber's SpiNNaker architecture [60].

All of the abovementioned approaches are validly called large-scale brain simulations but constitute very different forms of research of which not all might be suitable for Brain-Like AI design. According to H. Garis, the first two categories are adequate to serve as components of brain-inspired cognitive architectures or other AI systems. Simulations in the third and fourth category are useful for guiding neuroscience or hardware development but are not directly useful for AI. Finally, the fifth category is not directly useful, neither for neuroscience nor AI, but it serves as “proof of principle” with the motivation to lead on to other, more directly useful work in later steps.

H. Garis points out that at present state of technology, large-scale brain simulations have proven to be useful mainly for refining equations used for neural and synaptic modeling and for helping to substantiate conceptual models of brain structures and functions by connecting these models with detailed electrophysiological data in working simulations. They inform us about the dynamics of brain regions and allow us to probe the complexity that underlies structures such as cortical columns and the emergent nonlinear coherence that arises when large numbers of neurons are appropriately coupled. Nevertheless, detailed brain simulations do not yet yield intelligent behaviors not only due to a lack of processing power of (still inadequate) hardware for simulation but more importantly due to a lack of knowledge of the intermediate-scale structure of the brain, so as to be able to encode it into simulations. Furthermore, an embodiment of brain signals seems to be important. However, this aspect has been seldom considered so far in brain simulations.

H. Garis et al. [41] indicate that in case large-scale brain simulation research programs were successful, the biggest benefits are still lying ahead including the followings:

1. Gathering and testing neuroscience data
2. Cracking the neural code
3. Understanding neocortical information processing
4. A novel tool for drug discovery for brain disorders
5. A foundation for whole-brain simulations
6. **A foundation for human-like Artificial General Intelligence**

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[17] http://www.humanbrainproject.eu/

Garis at al. [41] point out that it is not yet clear whether large-scale brain simulations will be the first approach to lead to success in human-like intelligence, but it is certainly a plausible and promising approach and different researchers in this field have set their long-term sights specifically in this direction.

(Brain-inspired) cognitive architectures

(Brain-inspired) cognitive architectures attempt to achieve brain-like functionalities by emulating the brain's high-level architecture without necessarily simulating its lower-level specifics [48]. The term *brain-inspired* (or *biologically-inspired*) *cognitive architectures* became common only within the last years through the DARPA funding program administered by the Information Processing Technology Office. Nevertheless, the basic concept of cognitive architectures itself is as old as the field of Artificial Intelligence. While there is no rigid demarcation that separates brain-inspired cognitive architectures from cognitive architectures in general, the term is intended to distinguish cognitive architectures drawing significant direct inspiration from the brain and those based exclusively (or nearly exclusively) on models of the mind [48]. While brain simulations are intended to display not only similar functions to a brain, but also closely similar internal structures and dynamics, brain-inspired cognitive architectures are mainly intended to display (still loosely) similar functions to a brain. They furthermore aim at displaying internal structures that are conceptually inspired by the brain (and not just the mind) but not necessarily extremely similar to it. In practice, drawing a connection between the organization and the activation patterns of the brain and functions of the mind that emerge from them is certainly still a highly challenging task. Thus, the "loosely similar functions to the brain" are in many cases still extremely loose and it is doubtful if these approaches should actually be labeled as "brain-inspired cognitive architectures" or rather simply as "cognitive architectures". In their survey of cognitive architectures, W. Duch at al. [36, 48] divide existing cognitive architectures into three paradigms:

1. **Symbolic Architectures:** Symbolic paradigms follow a long tradition in AI and are based on the assumption that the mind exists mainly to manipulate symbols that represent aspects of the world or themselves [93]. Examples for symbolic architectures are amongst many others SOAR [66], EPIC [105], ICARUS [69], NARS [145], or SNePS [113]. In [48], they are considered to be psychology-inspired cognitive architectures instead of brain-inspired approaches. While symbolic architectures contain many valuable ideas and have yielded some interesting results, it is doubtful whether they will give rise to the emergent structures and dynamics required for human-like general intelligence.
2. **Emergentist Architectures:** Emergentist cognitive architectures consider abstract symbolic processing to result and emerge from lower-level subsymbolic dynamics, which are in most cases biologically inspired up to a certain extent. They are designed to simulate neural networks or other aspects of human brain function [48]. A few examples for emergentist architectures are HTM [51], DeSTIN [9], IBCA [102], Cortronics [117], or NOMAND [37]. Furthermore, there exists a set of emergentist architectures focused specifically on developmental robotics [74] to control robots without significant „hard-wiring" of knowledge and capabilities. Here, robots learn via their engagement with the world [48]. Examples for existing architectures are DAV [49], SAIL [148], FLOWERS [11], and IM-CLEVER [81]. Similar to classical AI connectionist systems, emergentist cognitive architectures have proven to be strong in recognizing patterns in high-dimensional data, reinforcement learning, and associative memory. However, probably due to their so far only quite superficial analogy to brain circuits, they have not yet led to the emergence of any brain-like functions [48].
3. **Hybrid Architectures:** Due to the complementary strengths and weaknesses of symbolic and emergentist approaches, researchers have started recently to focus on integrative, hybrid architectures. These combine subsystems operating according to the two different paradigms

described above [48]. Combinations have been suggested in many different ways. Examples are the connection of a large symbolic system with a large subsymbolic system or the creation for populations of small agents, each of which is both symbolic and subsymbolic in nature [48]. Examples for hybrid cognitive architectures are CLARION [120], DUAL [88], LIDA [40], ACT-R [71], MicroPsi [10], Polyscheme [23], 4CAPS [58], Shruti [114], the Novamente AI Engine [43], 4D/RCS [2], or OpenCogPrime [47]. In [89], N. Nilsson claims that *"AI systems that achieve human-level intelligence will involve a combination of symbolic and non-symbolic processing."*

Résumé

In summary, as outlined by B. Goertzel at al. in [47], today, *"brain simulations tell us about cortical columns and about the way collections of neurons "spontaneously" organize into collectives, but they do not yet tell us anything specific about how brains achieve goals, select actions, or process information. On the other hand, (brain-inspired) cognitive architectures tell us how brains may do things, but so far their intelligent behaviors are quite simplistic compared to real brains."* They consider three possible future directions that could lead to the emergence of human-like Artificial Intelligence:

1. Large-scale brain simulations, which simulate multiple brain regions and their interconnections, thus verging on being brain-inspired cognitive architectures.
2. Brain-inspired cognitive architectures, which integrate more detailed neural dynamics into their processing, enabling greater creativity and flexibility of response.
3. Hybrid architectures that link brain-inspired cognitive architectures elements with brain simulation elements.

B. Goertzel at al. give preference to the third option and argue that this will be the most rapid approach towards the twofold goal of understanding the brain and emulating human-like intelligence in computers. In principle, this approach can be considered as an addressing of the problem of emulating the brain by a combined bottom-up neuroscientific and top-down cognitive approach. With this, it is hoped to learn more about the crucial intermediate levels of cognition, about which the least body of knowledge is available currently [45].

7. General challenges and stumbling blocks

Considering the potential benefits of using the brain as an archetype for intelligent system design, it is at first glance surprising that so far only relatively limited attention has been paid to this approach in the field of Artificial Intelligence in comparison to merely mathematically and algorithmically guided concepts. Of course, attempts for the design of Brain-Like AI have existed since the very beginning of AI – with its most popular example being artificial neural networks (see Chapter 5). However, up to now, inspiration from the brain has mainly been drawn just on an abstract level not really justifying the label "brain-like" or "brain-inspired" intelligence [137]. As discussed in the following sub-sections, the reasons for this are multiple. While part of them are purely scientific challenges, others have a more "socio-political" character based on different views, perceptions, and ideologies of different AI researchers. The following points seem obvious once they are as explicitly formulated as it is done in this article. However, in the past, the issues AI researchers chose to investigate led to considerable confusion and misunderstandings, particularly amongst younger researchers having entered the field of AI only once it was already as diverse and heterogeneous in its objectives, methods, and ideologies as it is today. I myself at the beginning of my scientific career can be included into this group. Thus, outlining the challenges to face and the stumbling blocks to overcome can be very valuable for the sake of better clarity and to avoid a repetition of errors that could have been avoided by learning from the past.

7.1. Decipher the complexity of the brain

The most important reason for the quite limited "brain-inspiredness" of existing AI approaches lies most certainly in the complexity of the brain and the difficulty to understand it. Existing models in brain sciences are often still only abstract and descriptive instead of a functional character and contain blank spots and inconsistencies. T. Deutsch [34] describes the problem as follows: *"Various sciences have gathered a vast amount of information on the human mind. An unmanageable flood of different theories, ideas, and approaches derived from psychology, neurology, and philosophy could be used as starting points. The problem is: They are piecemeal – no holistic model is provided."*

What is particularly missing is an understanding of the intermediate levels of cognitions, i.e., how neural correlates can actually result in cognitive functions. B. Goertzel [45] formulates this problem as follows: *"On the one hand, the cognitive sciences provide very clear advice regarding what the overall "conceptual architecture" of an Artificial General Intelligence (AGI) system should be like ... We know what the major regions of the brain do, and we also have a decent working decomposition of human cognition into a list of interacting yet significantly distinct faculties. This high-level architecture can be emulated in AGI systems. On the other hand, the cognitive sciences provide a variety of suggestions regarding specific low-level mechanisms for carrying out intelligent processing, such as perception, learning, and memory. However, the low-level messages from the cognitive sciences are more controversial than the high-level ones for two reasons. First, there is less agreement on them among contemporary experts. And second, it's not always clear that emulating human psychological or neural behavior is a practical approach to implementing intelligence on radically un-brain-like hardware. Cognitive theorists recognize that there is more to the human mind/brain than its high-level architecture and low-level mechanisms. However, the cognitive sciences to date have had relatively little to say about the crucial "intermediate level" of intelligence. This is the main reason that the cognitive sciences don't yet provide really powerful prescriptive guidance to AGI designers. The cognitive sciences tell us what major parts a mind/brain should have, and they describe some low-level mechanisms that can help these parts to carry out their functions, but they say precious little about how the different parts all work together, and how the low-level mechanisms coordinate to give rise to higher-level dynamics."*

M. Looks and B. Goertzel [73] further indicate: *"The best approach to Strong AI at present, we suggest, is to learn what we can from the brain about what sort of high level architecture and general dynamics and representations are useful for achieving general intelligence under conditions of limited computational resources – and then fill in the algorithmic level with representations and algorithms that make sense in terms of the mathematics, computer science, and computer hardware and software that we know. This attitude leads into an integrative approach to AI, in which one takes a general architecture loosely inspired by human cognition, and then uses it to bind together components drawn from various areas of mathematics and computer science."* The suggestion to fill blank spots with algorithmic solutions is without doubt reasonable and valid to achieve functioning systems. However, this approach has to be followed with caution as it has in practice led to further problems (see Section 7.5 for further details). In summary, researchers that aim at emulating brain functions for technical purposes need, apart from sophisticated skills in engineering, a relatively profound understanding of the state of the art knowledge in brain sciences. Apart from this, they need the analytic capacity to detect inconsistencies and blank spots in brain theories and the ingenuity and creativity to propose solutions how to resolve them.

7.2. Find the right level of abstraction and detail

A second point crucial to successful brain modeling is the specification of the right level of abstraction and detail from which to start. This decision certainly depends on the specific requirements of the system in mind (e.g., what processes need to be explained by the developed model). Starting with a neuroscientifically inspired bottom-up design (as in large-scale brain simulations) on a level with too much detail – e.g., with the modeling of molecular processes in single neurons when trying to understand the general information flow in larger cortex structures – bears the danger of becoming lost in unnecessary details not directly relevant for the given problem. Similarly, starting with a top-down design (as generally in cognitive architectures) and remaining with brain analogies on a too high level of abstraction can lead to models that are too loosely patterned in regards to the organization and principles of the brain. Such designs tend to contain rather simplistic metaphors instead of sound models of the brain/mind. In such approaches, researchers are in danger of falling back to classical AI methods and developing solutions of mere mathematical and algorithmic character. In this context, O. Sporn [118] comments that *"it will be futile and scientifically meaningless to attempt to build intelligent systems by slavishly imitating or replicating the real brain. On the other hand, the extreme computational functionalism of the classical AI movement has done little to advance flexibility and robustness in intelligent systems. What is needed is a new synthesis of brain, cognitive and engineering sciences to harness the complexity of biological systems for the design of a new generation of more capable brain-like intelligence."* Similarly, in his article about *Neuroscience and AGI*, R. Koene [61] points out that *"a recurring argument against borrowing from neuroscience in the development of AGI has been to note that the low-level design of the brain is very complex, possibly needlessly complex for general intelligence. But other difficulties arise when one instead chooses the most obvious alternative approach: Observing high-level processes and implement those"*. He raises his concerns about the strong reliance on vastly simplified models of cognition in AGI: *"The aspects of cognition that are well-explained by the popular cognitive architectures cited in AGI research are based, in part, on cherry-picked experiments and corresponding data about human cognitive processes that are the easiest ones to characterize."*

7.3. Overcome the lack of interdisciplinarity and collaboration

A further possible reason for the limited progress in Brain-Like AI so far can be found in the fact that many AI researchers – who are still mainly computer scientists and engineers – naturally lack deeper understanding of established brain theories. Obtaining this knowledge, e.g., by regular and tight cooperation with brain researchers, could in the future make a huge difference. However, setting up fruitful interdisciplinary collaborations which would benefit from synergies still requires considerable effort. In his article *What Can AI Get from Neuroscience*, S. Potter [99] states: *"Yet, little attention in the AI field has been directed toward actual brains. Although many of the brain's operating principles are still mysterious, thousands of neuroscientists are working hard to figure them out. Unfortunately, the way neuroscientists conduct their research is often very reductionistic, building understanding from the bottom up by small increments. A consequence of this fact is that trying to learn, or even keep up with, neuroscience is like trying to drink from a fire hose. General principles that could be applied to AI are hard to find within the overwhelming neuroscience literature. AI researchers, young and old, might do well to become at least somewhat bilingual."* He further suggests: *"It's time for AI to move in the brainwards direction. This could involve PhD programs that merge AI and neuroscience, journals that seek to unite the two fields, and more conferences at which AI researchers and neuroscientists engage in productive dialogs. Neuroscientists have not exactly embraced AI either. Both sides need to venture across the divide and learn what the other has to offer."* Similarly, B. Sendhoff et al. [111] point out: *"New principles are usually found at the interfaces between existing disciplines, and traditional boundaries between disciplines have to be broken down to see how complex systems become simple and how the puzzle can be assembled. Each of us is rooted in a certain community which we have to serve with the results of our research. Looking beyond our fields and working at the interfaces between established areas of research requires effort and an active process. It is our belief that we have to more intensively pursue research approaches that aim at a holistic and embedded view of intelligence from many different disciplines and viewpoints."*

A further fact that contributes to the problem is that researchers who are actually active in the field of Brain-Like Artificial Intelligence are currently still located on the borders of other disciplines. So far, they have spent only moderate effort on collaborating amongst each other. To catalyze the emergence of the field of Brain-Like AI, it will be necessary that they start to join forces.

7.4. Avoid a misapplication of terms

The domain of Brain-Like Artificial Intelligence is still relatively new and dynamic and only beginning to establish. It is up to now no homogenous research field with well-defined borders and it must struggle with many difficulties and barriers in addition to the ambitious challenge of understanding and emulating the brain based upon incomplete knowledge from neuroscience, cognitive sciences, and other disciplines.

One problem with this field that has led to considerable confusion not only amongst the general public but also amongst AI researchers themselves is that there do not exist guidelines or rules for when a model may be called "brain-like" or "brain-inspired". There are no broadly accepted definitions that define the attribute "brain-like" and how the attribute can be implemented and tested [53]. B. Sendhoff et al. [111] state: *"What is Brain-Like Intelligence? Although it seems necessary to have a good understanding of what one wants to create before one starts, there is no crisp and clear definition."* Unfortunately, the term "brain-like" is therefore sometimes misapplied or misused either knowingly or unknowingly. Knowingly, this happens for marketing purposes – as the label brain-like (or similar) is often (partly unconsciously) perceived as a synonym for highly sophisticated and advanced hardware and software technology amongst the general public. On the other hand, in the past, this has also occurred partly unknowingly due to engineers' and computer scientists' limited understanding of the difference between the structure and information processing principles of the brain and commonly used computer architectures and programs.

In both cases, this has sometimes led to a mere transfer of terms from brain sciences to AI rather than a transfer of sophisticated concepts and principles. T. Deutsch [34] advises caution in this context: *"One has to be careful when using terms from human sciences. They tend to end as a label for something, which has nothing to do with the original concept they described"*. Several textbooks, articles, and PhD theses written in the past have shown that a conclusive and tight merging of biological and technical concepts is not that straightforward. There exists literature that starts with a description of biological, neural, and cognitive principles in the first chapters and finishes with technical solutions in the last ones without a direct, notable correlation and connection between the former and the latter [5]. In other approaches that claim to be brain-inspired, some correlations between certain mechanisms in the brain and the developed models can be deduced. However, what is still often missing is a clear statement about which parts of the models have taken inspiration from the brain and which elements were guided by mathematic-algorithmic methods and engineering considerations only [100, 107, 121].

7.5. Prevent a drive against the traffic

While Brain-Like AI generally aims at implementing concepts from the brain for the design of technical systems, there exists on the other hand a research niche where engineers aim at understanding the brain by studying the structure and behavior of common (not brain-inspired) computational systems and programs [8]. Although such approaches can in certain cases bring some new interesting insights [111], in practice this has on occasion been counterproductive in the past as it has misguided researchers who did not have a clear picture of the differences between today's computational machines and the brain [137]. It should be noted that – if these computational systems and programs were not designed by taking inspiration from nature and the brain/mind – it is scientifically "dubious" to draw conclusions about the functioning of the brain from these designs, at least, without further consultation with brain scientists and their theories about brain function. L. Miller states that AI researchers have to be criticized for this in particular as this has not produced theories whose adequacy can be tested by empirical research [82]. M. Looks and B. Goertzel [73] formulate this criticism in a more moderate way: *"We are neutral as to how directly the brain's* *neuronal network structure and dynamics relate to its cognitive representations and algorithms, and also as to how closely the brain's knowledge representation resembles formal logic and how closely its dynamics resemble logical inference. These are very important questions, but neuroscience has not yet progressed far enough to give us the answers. No one knows how an abstract proposition like "Every boy has a dog that every girl likes to call by a special name" is represented or manipulated or learned through experience in the human brain, and until we know this, we won't know the extent to which the conceptual premises of the most popular neural net or logic based approaches to AI are correct."*

To be fair, it has to be mentioned that there has started to evolve a research niche called *AI-Inspired Biology* [24] where cognitive scientists and biologists have joined forces with AI researchers with the aim to illustrate ways in which AI can influence research on natural cognition and formulate new research questions in biology and brain sciences. Treating such topics in an interdisciplinary team instead of just amongst engineers certainly has higher probabilities of success.

7.6. Tolerate and respect differences in scientific ideology

Artificial Intelligence is not a homogeneous research domain but actually deeply divided into sub-fields with different ideologies, methodologies, and targets. It requires a profound understanding and knowledge about the history and developments in AI to gain an awareness (and maybe also tolerance) of the differences in approaches and aims of the distinct sub-disciplines. This fact is particularly problematic in the field of Brain-Inspired AI. While other AI domains are focused on approaches based on mathematic, algorithmic, and computation theories, Brain-Like AI aims (or at least should aim) at using the (human) brain as archetype. It therefore has different objectives and methodologies and targets an absolutely different level of complexity than the mathematic-algorithmic approaches of the more "classical" AI. The problematic of the differences in objectives, ideology, and methodology of different AI domains comes into play when a researcher of one sub-field evaluates the work of a researcher of the other sub-domain. In practice, it seems to happen rather frequently that editors and funding agencies assign research articles or scientific research proposals to reviewers with an "opposing ideology" about how research in AI should be done. In certain cases, this can lead to a misinterpretation and at times an unjustified rejection of scientific work of related but opposing disciplines. This phenomenon is not particularly new in AI (and is probably also common in other fields of science). Furthermore, like today, already in 1960, the competition for research funding in AI was intense. As pointed out in [70], there have thus always been personal animosities between AI researchers of different groups. In 1969, for instance, M. Minsky and S. Papert published their famous work on *Perceptrons* [84] criticizing computational models of the nervous system, which showed *"with unanswerable mathematical arguments that such models were incapable of doing certain important computations"* [70]. This killed most research in neural computing for the following 15 years. Much later, S. Paper admitted in an interview [70]: *"Yes, there was some hostility behind the research reported in Perceptrons ... part of the drive came from the fact that funding and research energy was dissipated ... money was at stake."* In recent times, these conditions have turned out to be particularly hard for scientists working in Brain-Inspired AI. As they are still a minority compared to other AI research communities, the statistical probability that their work is judged (and sometimes misjudged) by experts of opposing fields is relatively high. Of course, misjudgment of scientific quality of work does not only occur in a one way direction from classical AI to Brain-Like AI but also the other way around. A. Sloman [111] points out that *"lessons learned from and within classical Artificial Intelligence remain relevant to the research program of creating brain-like intelligence and the reaction against everything related to classical AI may even have held up progress."* However, as the field of Brain-like Artificial Intelligent is still very novel and dynamic and can so far only count on a small community of researchers compared to traditional AI, it is in this case still a quite unequal fight, which can drastically slow down necessary progress.

7.7. Establish suitable measures for validating progress and success

As in any other field of engineering and science also in Brain-Like Artificial Intelligence, the validation of progress and success is a crucial element [112]. In Brain-Like AI, the aims, methodologies, and the level of complexity of problems are different from other fields of AI. Accordingly, different evaluation mechanisms for judging the value and success of developed approaches have to be found.

Applied AI tries to achieve some kind of computational behavior that can solve mainly circumscribed and limited problems that would need cognitive capabilities when done by humans. Brain-Like AI aims at using similar organizational structures and information processing principles like the brain to achieve such tasks. For example, it is impossible to isolate the "person-recognition-brain-circuits" from the "fruit-recognition-circuits" or the circuits for planning a travel route from the ones taking a decision about what to eat for breakfast. Thus, Brain-Inspired AI cannot focus on isolated problems. It has to aim at solutions targeting human cognitive capabilities at a more general and global level. It has to target topics such as human perception, situation assessment, or human decision-making in a more holistic way and cannot just focus on singular topics such as "face recognition" or "path planning" in a specific context.

In Applied AI as it focuses on very specific and circumscribed problems, an evaluation and comparison of results amongst each other is relatively straightforward. For example, for a particular classification problem, the number of true and false positives can be determined and compared in different approaches. A qualitative comparison of machine performance with human performance is generally out of the scope of the evaluation.

In contrast, in research fields like Brain-Like AI and also Artificial General Intelligence (AGI), things are not that straightforward. In AGI (before Strong AI), which has been around since the beginning of AI, the challenge of effectively evaluating performance has been troublesome for scientists for decades. Strong AI has the aim of achieving a general level of intelligence instead of just measuring the performance of an approach in very specific sub-tasks. A. Adam [1] comments that *"if the aim of AI is primarily to create an artificial mind, then the success or failure of the whole AI project should be judged against this one goal"*. S. Legg [72], who provides an extensive overview and discussion of suggested methods for measuring biological and artificial intelligence, points out that the first fundamental problem for judging artificial intelligence is that *"nobody really knows what intelligence is"*. R. Davis [30] claims that the basic question is not just "What is intelligence?" but equally important also "Why is intelligence?" R. Sternberg et al. [119] point out that *"viewed narrowly, there seem to be almost as many definitions of intelligence as there were experts asked to define it"*. This problem is certainly "*especially acute when we need to consider artificial systems"* – e.g., the computer – *"which are significantly different to humans"* [72]. In the past, the most prominent approach for evaluating „intelligence" in the field of AGI (before Strong AI) was the Turing test, originally suggested by A. Turing in 1950 [123]. According to the Turing test, a machine is "intelligent" if a human judge cannot distinguish its answers from the answers of a person in a communication without direct physical contact. However, in later years, the Turing test has been heavily criticized [147] and has been subject to further changes and extensions, e.g., the total Turing test [106] which also incorporates video signals and the possibility to pass physical objects "through the hatch" to allow the interrogator to evaluate the subject's perceptual abilities and its "manipulative" abilities. This has led to an extension of earlier efforts using computer vision and robotic object manipulation. However, passing such extended Turing tests can just be – if at all – a necessary but not a sufficient condition for intelligence [85]. The Turing test is based upon the (doubtful) assumption that *"once having a sufficiently precise theory of the mind, it becomes possible to express this theory in a computer program. If the program's input-output behavior matches corresponding human behavior, this is evidence that some of the program's mechanisms could also be operating in humans"* [106]. One major problem with the whole Turing test is that it can just check for an indistinguishability of human behavior and the „behavior" a program emits in a particular situation. However, it is important to note that just because two things are indistinguishable from a certain perspective, they do not at all have to be the same. Judging progress and success in AGI thus remains a hotly debated issue.

Similar to AGI, finding adequate evaluation mechanisms in Brain-Like AI is a puzzling task. Like in AGI, the objectives in Brain-Like AI are much more complex than in Applied AI. Therefore, it is much more difficult to achieve quantitatively comparable results in the short term. After all, in Brain-Like AI – if done properly and without too many "workarounds" – the overall functionality of a model only starts to emerge when the whole system starts to sufficiently resemble the organizational structures and information processing principles of the brain. Furthermore, a detailed comparison of the performance of developed brain-like models with methods used in Applied AI or other fields of engineering – as frequently requested from reviewers – is often simply not feasible due to the fact that the problems addressed with brain-like models often simply do not match in terms of complexity with problems addressed in Applied AI and related domains for the following reasons:

- **Unequal Performance Comparisons:** The aim of Brain-Like AI is usually to provide more general, "global" solutions and not only task-specific solutions as normally addressed in Applied AI. A brain-like model targets for instance the problem of (machine) perception in general [138] and not just the distinction of ten specific faces in a number of video frames or single images. Thus, research efforts spent until reaching a more global solution – which also needs cooperation with brain-sciences on unresolved questions of brain functioning – are certainly much higher. Quantitatively comparing this "general purpose" solution to a "single purpose" approach that is highly specialized and optimized to one single task is certainly not a fair competition if the evaluation concerns only the task for which the "special purpose system" has been optimized.
- **Lack of Systems to which to Compare:** Brain-Like Artificial Intelligence targets particularly challenges and applications for which today there are still no satisfactory solutions provided by current technical approaches. In order to compare a particular brain-inspired approach with other purely mathematically/algorithmically-based technical approaches for such a "complex" application, it would therefore be necessary to do both:
  1. Develop the brain-inspired approach;
  2. Develop, adapt, and customize purely technical approaches for the given non-trivial problem – developments that can, if done properly, themselves easily take several years or even decades for each chosen approach;

  This would however need an enormous effort that could only be achieved by combined major resource and time investments from various research groups with different backgrounds having a common interest in amicable competition. Applying for funding for such an undertaking seems to be however outside the current funding frameworks.
- **Different Requirements for Comparison from Different Disciplines:** Brain-Like AI faces an additional difficulty in comparison to other sub-disciplines of AI and engineering as it is very interdisciplinary. B Sendhoff et al. [112] point out: *"We are not clear yet, whether we shall position ourselves more within the scope of* brain *science or technology. In the first case, success has to be judged by neurophysiological or psychological experimental data as is the case in computational neuroscience. In the second case, the target is to provide evidence that the realized system accomplishes its intended requirements. Of course, in this case we have the initial burden to clearly define what the intended requirements are against which we want to judge our progress. The fact that there is a continuous transition between both extreme stand-points makes the measurement process even more ambiguous."*

Seeing the difficulties of quantitative comparisons of Brain-Like AI approaches to other conventional existing technical approaches and considering the fact that we are at the very beginning of the development of the field of Brain-Like AI make it necessary to reach for validation methods that are different from the ones common in more classical fields of engineering and Applied AI. As outlined above for the field of AGI which faces partially similar challenges, the discussion of how to do this is still ongoing. Nevertheless, the fact that in Brain-Like AI we can judge both "brain similarity" and "system accomplishment" – as indicated in point three of the itemization above – can actually be considered as an advantage concerning validation criteria in comparison to AGI. While AGI usually still has to rely on external observations of emitted „intelligent behavior" only (e.g., the Turing test), which has proven to be problematic, Brain-Like AI can additionally count on an analysis of internal similarities of developed models with the brain on a neural/cognitive level. Together with the emitted function of the implemented technical system, the analogies in organizational structures and information processing principles of the underlying model can be compared to the ones of the brain to obtain a judgment of its quality. It is important to note that an ideal brain-like model should show both similarities in externally emitted function and in internal organization and processing! Such an evaluation becomes particularly interesting if learning mechanisms are integrated into a model. If these learning mechanisms were actually sufficiently „brain-like", similar structuring and function principles should evolve after this learning as they can be observed in the developed (human) brain. In the long run, such "self-developed" similarities could be an ultimate proof for adequate brain-like design.

8. Recommendations for a way to go in future

As outlined in the last section, the field of Brain-Inspired Artificial Intelligence is not completely non-problematic for different reasons. While part of the difficulties are issues of "science-policy" and could therefore be addressed by broadening researchers' still sometimes a bit too one-sided view on the topic via a promotion of interaction between disciplines, the most severe drawback is still the fact that the brain is presently not sufficiently understood on all levels to technically emulate its complete function based on existing neuro-cognitive models alone. In the future, symbiotic developments of AI researchers together with brain scientists might be able to change this fact. However, this process will require time. B. Goertzel [45] describes this problem and suggests a possible way out of this dilemma as follows: *"Given the current state of the cognitive sciences, the present-day Artificial General Intelligence (AGI) designer has several recourses:*

- *Firstly, he can simply wait until the cognitive sciences advance further, and give more thorough prescriptions for AGI design.*
- *Secondly, he can ignore the cognitive sciences and attempt to design an AGI on other grounds – e.g. based on the mathematics of reasoning, or based on general considerations regarding the dynamics of complex self-organizing systems. Of course it's worth reflecting that many of these „other grounds" – such as mathematical logic – were originally conceived as qualitative models of human thought. But still, in spite of this historical fact and the strong intuitive feelings associated with it, the empirical cognitive sciences have not yet substantiated any deep connections between mathematical logic and human cognition.*
- *Or, thirdly, he can seek to create an AGI design that is consistent with the information provided by the cognitive sciences, but also introduces additional ideas filling in the gaps they leave."*

According to the understanding of Brain-Like Artificial Intelligence as followed here, the third suggested approach seems to be the most sensible one for the moment and is therefore the one advocated in this article. However, to avoid confusion, it should always be transparent which parts of the model are actually brain-inspired and which are those that are based on such „technical workarounds". Accordingly, my recommendation for a procedure to follow in the future for the development of Brain-Like AI systems is the following:

1. Use knowledge about the organizational structures and information processing principles of the brain as basis for model and system development as far as available.
2. Based on this, advance the knowledge in brain sciences by reporting detected inconsistencies and blank spots in existing brain theories.
3. In case the emulation of the brain is not possible at a certain point due to blank spots, supplementary logical engineering considerations are allowed to create a functioning technical system. However, it must always be pointed out clearly what "workarounds" have been used and at which place. In fact, such workarounds can in certain cases even enhance the knowledge about the brain by bringing up new hypotheses which have been missing in the big picture about the functioning of the brain. Nevertheless, one always has to be clearly aware of the balancing act of drawing conclusions from such technical solutions back to the brain. In the past, they have far too often led to inappropriate claims about the structure and functions of the brain.
4. Validate the model in terms of both achieved functionalities and similarities to internal structural organization and processing principles of the brain.
5. When having proposed a new potentially relevant hypothesis concerning particular brain functions, aim at bringing this hypothesis to the attention of the respective discipline of brain science (e.g., via peer-reviewed journal publications) with the encouragement to experimentally verify it with empirical brain science data.

During the process of increasing the synergies between Artificial Intelligence and brain sciences in the way proposed above, a bootstrapping process is likely to occur. Brain research will provide better models that can serve as basis for more advanced AI systems. More sophisticated AI systems will give brain scientists the tools to make further discoveries and interpret them [99].

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