

Research Article

Implementation of AGI on Brain-Like Neuro-Network Structure

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Abstract

The proposed approach to creating AGI using brain-like neural networks combines principles that teach systems to effectively generalize, remember, plan, and reason across a variety of tasks, drawing on ideas from neuromorphic architectures, dynamic hierarchical information processing, and hybrid neural-symbolic methods. Brain-like architectures dynamically process event-driven information over time, provide online learning and low power consumption, and implement research projects on hardware-based implementation of online plasticity. Within the framework of brain-like neural networks, this involves hybrid approaches to world reconstruction and action planning. The goal is to enable the network to reason, manipulate symbols, and use rules, similar to natural intelligence. This is achieved using differentiable logic, modal induction, neural memory processors, neural program interpreters, and neural-modular networks for task composition. This improves long-term memory, planning, and reasoning accuracy with a limited training set. It also enables skill transfer from one task to another, simulating alternative actions without multiple interactions with the real world. Brain-like neural networks have a modular, scalable architecture with routing and an ensemble of specialized modules. Neural modules for vision, planning, dialogue, and motor control can be dynamically assembled without complete retraining. Memory, planning, and perception are separated into separate modules with mechanisms for collaboration and joint goal learning. AGI based on brain-like neural networks enables knowledge transfer across domains. Neuromorphic modules motivate themselves to explore and investigate the environment, which supports long-term adaptability, similar to biological mechanisms. This is essential for AGI to function in the real world.

Keywords

AGI, Brain-like Neural Network, Neuromorphic Modules, Information Structure

1. Introduction

Research into AGI implementation addresses aspects of how to approach natural intelligence. Let's consider current approaches and challenges:

1. AGI Functionality:

AGI (Artificial General Intelligence) is a system capable of solving a wide range of tasks at human-level or better, learning and adapting to new tasks without specific reconfiguration,

transferring knowledge between domains, and operating autonomously.

2. Technological Approaches to AGI:

1) Multimodal Models: Large Language Models (LLM) and multimodal models achieve increasingly complex and extensive capabilities, performing cross-task and planning at a level previously considered impossible

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Received: 19 September 2025; **Accepted:** 28 September 2025; **Published:** 12 November 2025



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[1-3]. However, they require enormous amounts of data and computation.

- 2) Agent-based approaches with tools that can generate text, plan, make decisions, act within an environment, and invoke external tools (the internet, computing services, robots) are one of the most discussed paths to AGI [4-7].
- 3) Modular and hybrid architectures, combining neural networks with symbolic methods, planning, and world models for understanding structures [8-16].
- 4) Minimal learning and long-term memory: continuous learning, learning with the required number of examples, and storing and using long-term memory are key challenges for adaptivity. - Security and balancing the controllability and transparency of AGI are relevant aspects.

3. Main research areas:

1) Scaling and learning on basic tasks:

- i. Linguistics, training signals, RLHF (reinforcement learning on human feedback), multimodal learning.
- ii. Examples: development of language models, models that work with text, images, and sound; attempts to develop intellectual skills from data from a wide range of tasks.

2) Agent-based architectures and tool exploitation:

- i. Architectures where an agent can plan, make decisions, and invoke external tools (code, APIs, knowledge bases, robotics).
- ii. ReAct approaches, agent tools (LangChain, etc.), integration of memory and real-time learning.

3) Modularity: neural networks + symbolics:

Learning and exploitation of cause-and-effect relationships, abstractions, and logical inference. Neural-symbolic AI approaches, integration of planning and reasoning.

4) World models and the universe:

Self-learning without direct interaction (dreaming, world models), environment modeling, and predictive planning.

5) Continuous and efficient learning:

Lifelong learning, the ability to learn without retraining or forgetting information.

6) Security, alignment, and manageability:

- i. Anti-malware, transparent decision making.
- ii. Research on secure deployment, behavior monitoring, deviations, and corrections.

4. Important tasks and metrics for AGI-oriented research:

- 1) Generalization and adaptation: the ability to transfer skills between unrelated tasks and work in unfamiliar environments.
- 2) Long-term planning and intelligent real-time behavior.
- 3) A wide range of competencies: action planning, learning new tasks with a minimal number of examples, working with tools.
- 4) Robustness and resistance to distribution shift.
- 5) Interpretability and understanding of the system's rationale for decisions.

- 6) Security and control: preventing malicious behavior, control monitoring, and secure updating.
- 7) Economic and computational resilience, training efficiency, and energy efficiency.

OpenAI's current achievements are aimed at improving model capabilities, behavior alignment, and safety, as well as developing tools and an ecosystem around large language models. These results are considered steps toward more general intelligence, but full-fledged AGI has not yet been achieved. OpenAI's current achievements are considered progress toward AGI:

1) Expanding multimodality and generalization:

- i. Developing architectures and training methods that allow models to work with various data types (text, images, and in some cases audio) and perform cross-domain tasks.
- ii. Improving the ability to reason, plan, and execute complex tasks within a single dialogue.

2) Next-generation models and their capabilities:

- i. GPT-4 and subsequent versions (GPT-4o, etc.) demonstrate more robust instruction following, improved inference, multi-step problem solving, and adaptation to user context [16].
- ii. Expanded context windows, improved knowledge transfer between tasks, and improved instruction understanding.

3) Tools and integrations (tool use):

- i. Public ChatGPT Plugins ecosystem: access to external services and real-time data, enabling searches, bookings, external APIs, knowledge bases, and more.
- ii. Built-in development tools: code interpreters/Python environments (Code Interpreter/Advanced Data Analysis), enabling data analysis, visualization, and code testing directly during a session.
- iii. Ability to call external tools and services to improve the usefulness and relevance of responses.

4) Security, Alignment, and Accountability:

- i. Actively working on model behavior alignment: learning with human feedback (RLHF), testing safe modes and limitations, prototyping through external auditors and proto teams.
- ii. Development of usage policies, moderation, and monitoring mechanisms to reduce the likelihood of malicious or toxic responses.
- iii. Transparency wherever possible and collaboration with regulators and the community.

5) Deployment Reliability and Usage Management:

- i. Controlled access to models via APIs and enterprise products, including monitoring, secure modes, and updates.
- ii. Developer Tools and Integrators: Plugins, integrations with external data sources and services, access and security management.

6) Contribution to Research and Practice:

- i. Improved training and alignment methodologies that are applicable not only to a specific model but to a broader class of systems.
- ii. These achievements represent progress towards AGI through increased generality, autonomy, instrumentation, and secure behavior alignment.
- iii. OpenAI is focusing on model scaling, combined with alignment, security, and tools that enable models to truly help people across a wide range of tasks, and on the creation of GPT-5. GPT-5 builds complete projects from scratch. The model handles complex development tasks from start to finish and generates ready-to-use web pages.

The author proposed a neural network-based axiomatic solver coaching AGI method for solving scientific and practical problems based on their formulations and developed axiom systems. This method works with information understandable to specialists [17]. This method can be implemented more effectively using neural networks with a brain-like structure.

This article examines the process of activating information structure through thoughts and its formation within the brain's structure.

2. Activation of the Brain's Information Structure by Thoughts

Thoughts activate the brain's information structure through genomic modulation, network coordination, and synchronization of neural patterns to construct relevant representations from available information and guide processing.

1. Information generation:
 - 1) The prefrontal cortex (PFC) forms relevant fragments of information in working memory.
 - 2) Memory information activates sensory and long-term representations.
 - 3) The PFC and associated networks send signals to the appropriate areas of the sensory cortex, hippocampus, and association areas to enhance relevant features and suppress irrelevant ones.
 - 4) This impulse from above causes information patterns to be reorganized in accordance with the current thought.
2. Brain network coordination:
 - 1) The frontoparietal network (FPN) acts as a controller and coordinates interactions between the attentional networks (DAN), the DMN, and sensory areas.
 - 2) The DMN is activated during moments of internal thought or memory generation.
 - 3) The balance of attention and the internal thought generator, through networks, controls which representations are active and how stable they are.
3. Neural codes and temporal organization:
 - 1) Information is encoded as distributed patterns of neural network activity: dynamically, by frequency, and by

cooperation.

- 2) Brain oscillations (gamma, approximately 30–100 Hz: local processing; theta, approximately 4–8 Hz: coordination and working memory) serve as bridges for integrating information and maintaining memory content.
- 3) Synchronization and phase coordination between neural regions strengthen communication, allowing the joint representation and processing of relevant information.
4. The role of attention and working memory:
 - 1) Attention selects relevant elements and directs resources to their processing.
 - 2) Working memory maintains these elements active during the thinking process.
5. Learning and adaptation through neuromodulators:
 - 1) Dopamine, norepinephrine, and acetylcholine regulate the meaning of information: reinforcement of useful information, attentional adaptation, and synaptic plasticity.
 - 2) This allows brain structures to become more sensitive to useful information.
6. Resilience:
 - 1) Predictive coding: the brain constantly predicts sensory input, which forms stable information structures.
 - 2) The brain redistributes resources using optimized activity patterns.
 - 3) The PFC activates relevant areas; signals from the PFC are then sent to the parasympathetic and frontal areas for calculations; oscillations and synchronization maintain the desired patterns and suppress unnecessary ones.
 - 4) Visual lexical areas are activated under the influence of information.
7. Research
 - 1) Functional magnetic resonance imaging (fMRI) reveals changes in functional connectivity between the FPN, DAN, and DMN depending on the active thought.
 - 2) EEG/MEG studies demonstrate the temporal dynamics of oscillations and interregional synchronization during thinking tasks.
 - 3) Information theory and predictive coding models allow us to formalize how mutual information between activity patterns increases or decreases during thinking.

3. Formation of Information Structure on Brain Structure

The formation of information structure on brain structure during communication and learning combines neurobiological mechanisms, the brain networks involved, and their significance for the formation of corresponding representations and skills. The brain is organized into modules (visual, linguistic, motor, etc.) that actively interact through large-scale networks. Dynamic network configurations determine what information is available for conscious processing at a given moment. Information integration extends from local activity

patterns to global representations and access to memory, attention, and control. Information structure can be viewed as a graph, where nodes are regions and edges are connections; consciousness can be associated with specific graph configurations and their temporal dynamics.

1. Information Structure:

1) This is the set of distributed activity patterns and connections between neurons/transmission between regions that encode, store, and use information. During learning and communication, the brain constructs and reconstructs these patterns: it forms schemas, concepts, skills, linguistic representations, and social models.

2) Structures can be structural (anatomical connections) and functional (how brain regions are actively activated during tasks).

2. Brain structures:

1) Language communication:

- i. Left hemisphere: Broca's area (speech production) and Wernicke's area (speech comprehension).
- ii. Linguistic-cognitive networks: auditory cortex, temporo-occipital area, frontal cortex.
- iii. Dual network, linking language processing with working memory and control.

2) Knowledge construction:

- i. Medial prefrontal areas, temporo-parietal area, parieto-temporal areas.
- ii. Mirror neuron area: premotor/inferior gyrus and inferior parietal lobe — involved in imitation and understanding of others' actions.

3) Memory and learning:

- i. The hippocampus and medial cerebellum are involved in the formation of episodic and coherent memories.
- ii. Prefrontal cortex: planning, abstraction, working memory, attention control.
- iii. Basal ganglia: consolidation of habits and action sequences.

4) Network modulations:

- i. Default Mode Network (DMN): involved in internal models, scenography, planning, and memory association.
- ii. Frontoparietal Network (CEN): attention control, working memory, real-time decisions.
- iii. Salience Network: identifying important information and switching between processing states.

3. Mechanisms of information structure formation:

1) Synaptic plasticity:

- i. LTP/LTD (increase or decrease in synaptic strength) under the influence of repetitive stimulation patterns.
- ii. Important neuromodulators: dopamine (motivational learning and reward evaluation), acetylcholine (attention and learning).

2) Consolidation and Integration:

- i. New information is first encoded locally, then integrated into existing schemas through repetition, sleep,

and repetitiveness.

- ii. Connections between the hippocampus and the cortex are strengthened to associate context and meaning with new knowledge.

3) Information Encoding:

- i. Encoding can be feature-based (sensory characteristics) and semantic (meaning, context).
- ii. Distributed Encoding: different patterns across multiple regions when representing a single unit of knowledge.

4) Formation of Schemas and Concepts:

- i. The prefrontal cortex and associated networks form abstractions, hierarchical structures, and knowledge "chunks."
- ii. In language, this is manifested in the construction of lexical and syntactic schemas and the learning of new concepts and terms.

5) Social coordination and collaborative learning:

In human interactions, brains can synchronize (neural synchrony) between participants, which helps them agree on shared meanings and mental models.

4. Stages of the learning and communication process:

- 1) Perception and attention: identifying important information, filtering information from the environment.
 - 2) Encoding: forming local patterns in relevant areas.
 - 3) Consolidation: reinforcing changes through sleep, repetition, and linking to existing schemas.
 - 4) Extraction and application: using what has been learned in speech, dialogue, and decision making.
 - 5) Continuous adaptation: new examples and contexts reformat the network and schemas.
- ##### 5) Research methods and tools:
- 1) Neuroimaging: fMRI, EEG/MEG, DTI to study structural and functional connections.
 - 2) Network analytics: graph analysis, functional connectivity, dynamic causal inference (DCM), RSA for comparing representations.
 - 3) Models and computations: neural networks, brain-inspired learning algorithms, information theory (entropy, mutual information) to estimate how much information is processed and how it is transferred between regions.
 - 4) Practical applications: educational technologies based on neurofeedback, personalized learning, language and communication skills training.
 - 5) Total and causal stimulation: TMS (transcranial magnetic stimulation) and other methods to test the relevance of specific areas/networks.
 - 6) Modeling: theoretical models (IIT, GWT) and neural-generative models that attempt to recreate conscious patterns.
 - 7) Empirics of consciousness: experiments with unconscious and conscious stimuli, mindfulness tasks, and assessment of the content of consciousness.
 - 8) Scientific mapping and education on the comparative

role of networks and activation patterns for different types of consciousness.

- 9) Neural interfaces where signal awareness influences device control.
- 10) Clinical assessment of consciousness in patients.
- 11) Modeling consciousness using the information principles underlying consciousness, using neural networks.

4. A Neural Network with a Brain-like Structure

Building a neural network with a complete replica of the brain's structure and functions is impossible with current technology. A brain-like architecture can be designed with modular, hierarchical learning principles similar to those of neuroscience. PyTorch can be used as a basic code framework to get started.

1. Modeling a brain-like neural network:

- 1) Modularity and specialization: separate modules for perception, memory, planning, and decision making.
- 2) Hierarchy: sensory layers → association areas → control layer.
- 3) Recurrence: maintaining context and information.
- 4) Bottom-up and top-down connections for predictive processing and attention.
- 5) Coherence: sparse connections and dynamic activity.
- 6) Local learning and plasticity: STDP update rules combined with gradient-based learning.
- 7) Learning by prediction and context: predictive processing, error prediction, attention.

2. Modular architecture:

- 1) Specialized brain-like architecture based on modularity:
 - i. Input sensory modules are V1-like — convolutional or temporal encoders.
 - ii. Recurrent association areas (V2/IT) are like RNN/GRU/LSTM or SNN networks.
 - iii. Memory and prediction are PFC-like — a module with attention mechanisms, high-level representations, predictive modeling.
 - iv. Control/action selection module — problem solving, planning, motor skills.
- 2) Implementation options:
 - i. Traditional deep networks with recursive connections and attention (PyTorch/TensorFlow).
 - ii. SNN neural networks for more biologically plausible behavior, based on customizable libraries such as Nengo, Brian2, and BindsNET, on Loihi hardware.
 - iii. Predictive coding models at each level.
 - iv. HTM (Hierarchical Temporal Memory) as an approach to memory sequences.

3. Step-by-step Implementation Plan

3.1. Project Objective and Scope

Dynamic image processing, multimodal signals, planning and control, continuous learning, etc.

3.2. Architecture Design

- 1) Module division: sensor module, dynamics module, memory/prediction, decision/control.
- 2) Connection definition: low-level bottom-up and high-level control pathways, including feedback.
- 3) Definition of the neuron/model type in each module: CNN/MLP for the sensory chunk, GRU/LSTM/SNN for dynamics, small RNN or Transformer submodules for memory and attention.

3.3. Selecting a Training Method

- 1) Predictive learning (next step prediction loss) combined with local weight update rules (e.g., STDP pairing with gradients).
- 2) Continuous learning and activation sparsity to save energy.

3.4. Architecture Implementation

- 1) Implement a modular structure: multiple independent modules with clearly defined inputs and outputs.
- 2) Add a communication mechanism between modules (bottom-up, top-down, with an attention mechanism).

3.5. Training and Experimentation

- 1) Start with a simple dataset and a limited set of modules.
 - 2) Gradually expand the network by adding modules and increasing the complexity of the task.
- 3.6 Evaluation:
- i. Ability to learn new tasks.
 - ii. Efficiency in accuracy, speed, and energy.

4. Starter Architecture in PyTorch

- 1) Network structure: sensor module → dynamic module → memory/prediction → decision module.
- 2) Without biological precision, with a brain-like architecture.

5. Implementation Project

- 1) Sensor module: a small convolutional unit for encoding the input (images/spectrograms). - Dynamic module: a recurrent part (GRU/LSTM) for context retention.
- 2) Memory/prediction: an additional layer that forms predictions based on context and errors.
- 3) Control: a small layer for making decisions based on memory and the current input.
- 4) CortexModule class: contains the input layer and GRU/LSTM, returns the hidden state.
- 5) PredictiveLayer class: takes the hidden state and forms a prediction, returns the prediction error.
- 6) BrainInspiredNet class: assembles modules: sensor module, dynamic module, memory/prediction module, and decision module; implements bottom-up and top-down relationships.
- 7) Weight update: basic gradient step + local rules (e.g., a simple form of STDP: ΔW proportional to $\text{pre-activations} * \text{post-activations} - \text{decay} * W$). - Decision module — a linear layer with softmax.
- 8) Neuromorphic hardware and projects: Loihi (Intel), SpiNNaker.
- 9) Hybrid models with brain-inspired principles, scalable to modern neural networks.

5. Implementing AGI on a Neural Network Structurally Similar to the Brain

Implementing AGI on a neural network with a neuromorphic structure similar to the brain is a complex engineering challenge [18]. We will consider a design approach to such a project at the architecture, training, and security levels.

1. Project Vision:
 - 1) AGI (Artificial General Intelligence) is a system capable of mastering and performing a wide range of tasks in different domains without special reconfiguration.
 - 2) An inorganic neural network with a hardware architecture that mimics the brain using spiking neurons, asynchronous processing, and a local learning rule in real time.
 - 3) A brain-like architecture implemented on hardware such as Loihi, SpiNNaker, BrainScaleS, etc., with possible integration with traditional digital computing.
2. Key Aspects on the Path to AGI:
 - 1) Retraining on all task sets and in different contexts.
 - 2) Effective lifelong/continuous learning, without constant data transfer.
 - 3) World models and planning: the ability to build predictive models of the environment and plan long-term.
 - 4) Multimodal integration of perception, language, motor skills, and abstract thinking.
 - 5) Safety, goal compliance, behavioral predictability, transparency, and control.
 - 6) Efficiency of the neuromorphic platform.
3. Architectural integration of a brain-like neural network into a comprehensive AGI system:
 - 1) General principles:
 - i. Modularity: alternating modules for perception, memory, world modeling, reasoning, and action.
 - ii. Asynchrony and local plasticity: learning through local rules (STDP, reward-modulated STDP, etc.).
 - iii. Dynamics of information processing in short-term and long-term memory.
 - 2) Typical modular structure:
 - i. Input layer and neuromorphic sensory processing units.
 - ii. Representation and attention module: construction of compact representations and directed attention processing to relevant areas.
 - iii. Working Memory and Long-Term Storage Module: Maintaining context, learning through experience.
 - iv. World Modeling Module: Predictive world model.
 - v. Planning and Decision-Making Module: Generating actions based on the current state and plans, integrating with graph/logical modules.
 - vi. Innovative Learning Module: Meta-learning and curiosity-driven mechanisms for autonomously mastering new tasks.

vii. Neurosymbolic Reasoning Module: Hybrid architecture, where neural components process not only sensory but also logical representation (neuro-symbolic approaches).

viii. Control and Safety: Goal Achievement Verification Mechanism, Behavior Limiters, and the Possibility of Correction -> Retraining.

3) Example of module interactions:

Sensory Perception -> Representation -> Attention -> Working Memory -> World Model -> Planning -> Actions -> Correction -> Retraining.

4. Main approaches to learning and implementation:

- 1) Inorganic-based learning:
 - i. Spiking neurons and local rules (STDP, homeostatic plasticity).
 - ii. Reward-modulated learning: reinforcement via a signal from the external environment or a virtual simulator.
 - iii. Surrogate gradients for training complex modules in a hybrid architecture.
 - iv. Self-learning and self-organization: autoencoders, predictive coding, self-supervised learning on a continuous data stream.
- 2) Multimodal and multi-layered representations:
 - i. Joint learning across different sensors: vision, speech, movement, language.
 - ii. Models of the world learned through the prediction of future states and actions.
- 3) Continual/Lifelong learning:

Anti-forgetting architectural solutions: Elastic Weight Consolidation, extensible architectures, modularity, replay segments.

4) Integration with symbolism:

A combination of inorganic neural networks with elements of symbolic reasoning (logic, planning, knowledge graphs) is necessary for more robust knowledge transfer.

5) Reference tasks and worlds:

Diverse environments, robotics, simulated worlds, references with long-term planning, logic and reasoning, language interpretation.

5. Hardware Neuromorphic Platform:

1) Popular Trends and Options:

- i. Loihi/Loihi 2 (Intel): Hardware implementations of spiking networks with local learning support.
- ii. SpiNNaker: A scalable platform for large spiking neural networks.
- iii. BrainScaleS: Analog/fast simulations of spiking networks.
- iv. Other frameworks: Nengo, PyNN, Brian2 for prototyping spiking models on various platforms.

2) What to consider when choosing:

- i. Support for the desired types of neuromorphic learning (STDP, reward-modulated learning).
- ii. Power efficiency, throughput, latency.
- iii. Compatibility with simulations and development

tools.

- iv. Integration with standard CPU/GPU layers for hybrid architecture.

3) Integration with software tools:

- i. Simulation tools: NEST, Brian2, SpiNNaker API, Nengo.
- ii. PyTorch/TensorFlow simulators for hybrid domains.

6. Safety, Ethics, and Alignment - Fundamental Positions:

- 1) Correct Goals for AGI. - Safety of Autonomous Behavior in Unknown Environments.
- 2) Transparency and Control Measures (Logging, Auditing, Explanations).
- 3) Practical Approaches:
 - i. Built-in Behavior Mechanisms According to Specified Frameworks.
 - ii. Verification and Testing in Different Scenarios.
 - iii. Feedback Learning, Inspection of Root Causes, Risk Audits.
- iv. Tools for Interpreting Module Performance: Attention Mapping, Root Cause Analysis, Motivation Tracing.
- 4) Social Aspects:
 - i. Transparency of System Operations.
 - ii. Transparency of Data Sources and Training Signatures.
 - iii. Ethical Principles and Responsibilities of Developers.

7. Step-by-Step Development Plan:

Basic Lab: - Build a Neuromorphic System with a Pair of Modules: Perception and Simple Memory.

Experiment with local learning rules and basic tasks in a single domain.

1) Phase 1: Multimodality and a Basic World Model:

- i. Add multiple sensory streams and a rudimentary predictive model of the environment.
- ii. Implement simple planning tasks and long-term goals in a limited environment.

2) Phase 2: Continuous Learning and Curiosity:

- i. Develop a system capable of learning from multiple tasks without forgetting, add curiosity modules.
- ii. Strengthen the neuromorphic architecture for robust knowledge transfer.

3) Phase 3: Neural-Symbolic Integration and More Complex Reasoning:

- i. Introduce symbolic modules or knowledge graphs, integrate with neural network reasoning modules.
- ii. Develop long-term planning, generate goals and checks.

4) Phase 4: Security and Audit:

Implement comprehensive security checks, test in a variety of scenarios, and implement human feedback mechanisms.

5) Phase 5: AGI Pilot Demonstration (upon reaching maturity):

Demonstrations across multiple domains of adaptability and extensive structural reconfiguration with functional

complication of information dynamics through retraining [14, 19, 20].

8. Technological Implementation:

- 1) Neuromorphic platforms and their programming: Loihi, SpiNNaker, BrainScaleS.
- 2) Spiking neural networks, STDP, reward-modulated plasticity.
- 3) Neural-symbolic integration, hybrid architectures.
- 4) Predictive coding-based learning and self-training.
- 5) Tools and Libraries:
 - i. Nengo, Brian2, NEST for spiking network modeling.
 - ii. SpiNNaker API, Loihi SDK for real hardware.
 - iii. Tools for simulating and analyzing modular system behavior.
- iv. Spiking networks and predictive coding.
- v. Lifelong learning without forgetting.
- vi. Neuro-symbolic integration and hybrid architectures for AGI.
- 6) Neural network axiomatic solver coaching AGI method for solving scientific and practical problems based on their formulations and developed axiom systems [17].

6. Conclusion

Creating an AGI with a brain-like architecture is a pressing experimental challenge. It is possible to build a flexible, scalable "brain-like" system based on modern technologies that approximates some aspects of AGI: task diversity, autonomous learning, planning in an unknown environment, memory, and adaptation. A brain-like neural network as a system operates on key principles of brain function: information dynamics, sparse connectivity, plasticity with local learning rules, and energy efficiency. Today, this is achieved primarily in two ways: first, by modeling with spiking neural networks (SNNs) on neuromorphic chips; second, by hybrid approaches, where modern deep networks are complemented by motivated bioinformatics systems. To date, no one has achieved practical AGI.

The brain-like axiomatic solver coaching approach facilitates progress toward AGI. A universal neural network axiomatic solver coaching method for solving scientific and practical problems based on their formulations and developed systems of axioms, implemented on a brain-like neural network structure, enables one to approach and surpass humans in the ability to acquire new knowledge and use it to build rational actions. The neural network axiomatic solver coaching method is proposed for implementation as a spark-process consciousness. The brain-like neural network is proposed for implementation as an artificial brain.

Specialists can describe a scientific or practical problem to be solved to the artificial consciousness using the PMT format. The artificial consciousness forms an information structure on the artificial brain. During the process of artificial thinking, the artificial brain generates either a reasoned solution or a reasoned answer—why the problem cannot be solved within the existing knowledge system.

Implementation of the Mega Project requires the formation of an international, interdisciplinary professional team of researchers, developers, and implementers. The implemented Mega Project can lead to the development and increased sustainability of human civilization.

Abbreviations

CFD	Contract For Difference
CSP	Constraint Problems Content Security Policy
CNN	Cable News Network
CVC	Card Verification Code
GPU	Graphics Processing Unit
GNN	Graph Neural Network
FOF	Fund of Funds
IDA	Interactive Disassembler Assembly
KPI	Key Performance Indicators
LISP	List Processing
NN	Neural Network
NSM	Naval Strike Missile
ODE	Ordinary Differential Equation
OKR	Objectives Key Results
PDE	Processing Development Environment
PDDL	Planning Domain Definition Language
PINN	Physically Informed Neural Networks
SAT	Scholastic Aptitude Test
SMART	Specific Measurable Achievable Relevant Time
SMT	Simultaneous Multithreading is a Technique
STRIPS	Separate Trading of Registered Interest and Principal of Securities
TPTP	Test & Performance Tools Platform
ViT	Vision Transformer
WOOP	Wish-Outcome-Obstacle-Plan
GDPR	General Data Protection Regulation
API	Application Programming Interface
AGI	Artificial General Intelligence
SDK	Software Development Kit
STDP	Spike-timing Dependent Plasticity
LSTM	Long Short-term Memory
HTM	Hierarchical Temporal Memory
RNN	Recurrent Neural Network
PFC	Phase-Fired Control
GWT	Google Web Toolkit
TMS	Transcranial Magnetic Stimulation
IIT	Integrated Information Theory
RSA	Rivest-Shamir-Adleman
fMRI	Functional Magnetic Resonance Imaging
EEG	Electroencephalography
DTI	Debt-to-income Ratio

Author Contributions

Evgeny Bryndin is the sole author. The author read and approved the final manuscript.

Conflicts of Interest

The author declares no conflicts of interest.

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