

Research Article

Automated Analytics by Models of Brain Based on Big Information and Artificial Intelligence

Evgeniy Bryndin* 

Research Center "NATURE INFORMATICS", Novosibirsk, Russia

Abstract

Researchers are actively exploring the relevance of automated information analytics using brain models. This field combines neuroscience, artificial intelligence, and machine learning, enabling a deeper understanding of information processing mechanisms in the brain and the development of more effective technologies. Scientists are creating mathematical and computer models that mimic brain functions. These models provide new insights into information processing mechanisms, particularly in the context of cognitive processes. Machine learning has become a powerful tool for analyzing large volumes of data generated in brain research. Machine learning algorithms allow for the estimation of parameters for models that reflect how the brain processes information. Neuromorphic computing mimics the functioning of the biological brain using spiking neural networks (SNNs). These networks transmit data using short pulses, allowing them to simulate natural signal transmission processes. Such systems offer high data processing speeds, can learn in real time, and can effectively solve problems such as speech recognition or image recognition in video sequences. Intel is developing neuromorphic processors, such as Loihi, that mimic the adaptive behavior of the brain. The intersection of neuroscience and artificial intelligence promises revolutionary advances in understanding the human mind and developing more complex and adaptable AI systems. Automated data analytics using brain models is a promising field that could lead to breakthroughs in neuroscience, medicine, technology, and other areas of human endeavor.

Keywords

Scientific Information, Artificial Intelligence, Multimodal Neural Network, Models of the Brain

1. Introduction

Automated analytics based on big informaton and artificial intelligence is a set of technologies for processing, analyzing, and interpreting large data sets using machine learning algorithms and other artificial intelligence methods [1-6].

1. Data collection:

- 1) sources: IoT devices, social networks, transactions, logs, sensors;
- 2) streaming and batch loading;

3) ETL processes (Extract, Transform, Load).

2. Storage and management:

- 1) distributed storage (Hadoop, Spark);
- 2) columnar databases (ClickHouse, Vertica);
- 3) cloud platforms (AWS S3, Google BigQuery, Azure Data Lake).

3. Processing and analysis:

- 1) parallel computing;

*Corresponding author: bryndin15@yandex.ru (Evgeniy Bryndin)

Received: 3 November 2025; Accepted: 12 November 2025; Published: 9 December 2025



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- 2) SQL analytics and NoSQL queries;
- 3) graph algorithms for identifying relationships.
4. AI modules:
 - 1) machine learning (classification, regression, clustering);
 - 2) Deep learning (neural networks, CNN, RNN, Transformers);
 - 3) Natural language processing (NLP);
 - 4) Computer vision (CV).
5. Visualization and reporting:
 - 1) Dashboards (Tableau, Power BI, Grafana);
 - 2) Interactive reports;
 - 3) Forecast charts and heat maps.
6. Decision automation:
 - 1) Recommender systems;
 - 2) Predictive analytics;
 - 3) Automatic triggers and workflows.
7. Typical use cases:
 - 1) Retail: Offer personalization, demand forecasting, inventory management.
 - 2) Finance: Borrower scoring, fraud detection, algorithmic trading.
 - 3) Manufacturing: Predictive maintenance, supply chain optimization.
 - 4) Healthcare: Image diagnostics, epidemic forecasting.
 - 5) Telecom: Customer churn analysis, network optimization.
 - 6) Marketing: audience segmentation, A/B testing of creatives.
8. Advantages:
 - 1) Speed: processing terabytes of data in minutes.
 - 2) Accuracy: reducing human error, identifying hidden patterns.
 - 3) Scalability: analyzing data of any size.
 - 4) Forecasting: scenario modeling and trend prediction.
 - 5) Autonomy: minimizing manual labor in routine tasks.
9. Challenges and Limitations:
 - 1) Data quality: need for cleansing and normalization.
 - 2) Infrastructure costs: powerful computing resources.
 - 3) Interpretability: "black boxes" of neural networks.
 - 4) Privacy: compliance with GDPR, Federal Law 152, and similar regulations.
 - 5) Talent: shortage of data science and MLOps specialists.
10. Trends for 2025:
 - 1) AutoML: automated model building and tuning.
 - 2) Explainable AI (XAI): transparency of AI decisions.
 - 3) Federated learning: data analysis without centralization.
 - 4) Real-time analytics: analytics with sub-1-second latency.
 - 5) Generative AI: creating synthetic data for model training.
11. Implementation Stages:
 - 1) Defining business objectives and KPIs.

- 2) Data and source audit.
- 3) Selecting a technology stack.
- 4) Prototyping and MVP.
- 5) Testing on real data.
- 6) Integration into business processes.
- 7) Monitoring and further training of models.

Automated analytics powered by artificial intelligence transforms large volumes of information into strategic assets, enabling decision-making based on facts and expertise. The key to success lies in combining artificial intelligence methods with multimodal neural network models of the brain [7, 8].

Brain models for automated analytics include both biological and mathematical models, as well as machine learning methods used to analyze brain data. These approaches are used in neuroscience, medicine, cognitive research, and the development of neuromorphic systems. Let's consider the key areas:

Mathematical and biological models of the brain:

1. Kuramoto model with extensions: Researchers from the Baltic Center for Neurotechnology and Artificial Intelligence extended the standard Kuramoto model to include high-order interactions (up to three elements simultaneously). This allows them to model the synchronization of neural networks and their transitions between normal and pathological states (for example, epileptic seizures). The model takes into account the dynamics of resource consumption and restoration in the connections between neurons.

2. Hodgkin-Huxley model:

A key mathematical neural model describing the generation and distribution of action potentials in neural cells. It is used to study electrically excitable cells, including neurons and myocytes. The model takes into account ion channels and membrane potential dynamics.

3. Hopfield Neural Network:

A popular mathematical model in neuroscience that demonstrates the principles of memory in a network of unreliable elements. It is characterized by associativity, noise immunity, and distributed information storage.

4. The Virtual Brain:

A project using a mesoscopic approach to modeling large brain regions and their interactions. It is used in cognitive neuroscience and biomedicine, for example, to predict the outcome of epilepsy surgery.

5. BioUML:

A platform for the formal description and modular modeling of complex biological systems, including the cellular level. It is used to create epilepsy models and integrate with regional models.

6. Neuromorphic Computing:

A field that simulates the functioning of the biological brain using digital neurons and spiking neural networks (SNNs). Such systems simulate natural signal transmission processes and can learn in real time. An example is the Loihi neuromorphic processor from Intel Labs.

Thus, brain models for automated analytics encompass a wide range of methods—from fundamental mathematical models to applied machine learning algorithms and neuro-morphic systems. Their development opens up new possibilities in medicine, cognitive science, and artificial intelligence technologies.

This article describes the processes of recording and processing semantic, auditory, and visual information in the brain. Various brain models for information analytics are also discussed: first, a neural network model of the brain for the formation of information structures, second, a neural network information model of the brain, and third, a multimodal information model of the brain.

2. Information Retention in the Brain

The retention of semantic, visual, and auditory information in the brain is accomplished through a complex hierarchical system of the cerebral cortex, including primary, secondary, and tertiary areas.

Primary cortex areas:

1. Primary projection areas are responsible for receiving and analyzing elementary sensory signals from receptors. They have a clearly defined topographic organization:
2. The visual area is located in the occipital lobe. This is where the physical parameters of visual stimuli (brightness, color, shape) are analyzed.
3. The auditory area is located in the temporal lobes. It processes frequency, amplitude, and other characteristics of sounds.

Secondary cortex areas:

1. Secondary areas receive information from the primary areas and perform its generalization and further processing:
2. In the visual system, they synthesize individual elements into coherent images (e.g., object recognition).
3. In the auditory system, intonations, melodies, and words are analyzed.
4. The somatosensory system forms representations of the body's position in space.

Tertiary cortex:

1. Tertiary areas (areas where analyzers overlap) are located at the border of the parietal, temporal, and occipital lobes, as well as in the anterior sections of the frontal lobes. They perform integrative functions:
2. Integrate information from different sensory systems (for example, linking visual and auditory images).
3. Provide understanding of the meaning of perceived information, including semantic processing.
4. Participate in the development of complex cognitive processes: speech, memory, and thinking. Functional blocks of the brain:
 1. Provide conditions for mental activity.
 2. The block for receiving, processing, and storing information (the second block) unites the occipital, temporal, and

parietal regions, as well as their associative zones. Responsible for perception, memory, and the integration of sensory data.

3. The programming, regulation, and control unit (third unit) is located in the frontal lobes. It facilitates goal setting, action planning, control over their execution, and correction of results. Interhemispheric asymmetry:

- The left hemisphere is primarily responsible for verbal functions, analysis, sequencing of perceptions, abstract thinking, non-speech noise, spatial orientation, emotional perception, and holistic image perception. Broca's area (motor speech) and Wernicke's area (sensory speech) are located here.

Memory and information retention:

- 1) Short-term memory is associated with the activity of the frontal lobes and thalamus.
- 2) Long-term memory depends on the activity of the hippocampus and temporal cortex. The Peipetz circle (hippocampus - mammillary bodies - anterior nuclei of the thalamus - cingulate cortex - parahippocampal gyrus - hippocampus) regulates memory and learning processes.

Thus, information acquisition in the brain is a multi-level process, involving signal reception by primary areas, processing by secondary areas, integration by tertiary areas, and regulation by functional units. The interaction between the hemispheres and subcortical structures plays a key role.

3. A Neural Network Model of the Brain for Forming Information Structures

A neural network model of the brain for forming information structures uses neural networks and associated algorithms to model information processing processes based on neural network structures similar to those of the brain. This approach enables the creation of systems capable of self-organization, learning, and the formation of complex multimodal information structures based on the brain model.

Key characteristics of neural network models for forming information structures:

1. Abstraction and modeling: Mathematical and algorithmic methods are used to model cognitive processes such as perception, memory, learning, and decision making.
2. Information structuring: These models help automate the creation, organization, and updating of information structures, such as knowledge, hypotheses, and concept maps.
3. Self-organization: The ability to model processes in which systems independently form effective data structures based on input data.
4. Learning and adaptation: The models are capable of adapting to new data and changing conditions without the direct use of biological neural networks.

Neural network approaches:

1. Logical systems: Using logical rules to form structures

and logically process information.

2. Formal models: Models based on graphs, trees, and network structures that reflect relationships between concepts or data.
3. Clustering and classification algorithms: For automatic identification of structures in data.
4. Multiple-view models: Using multi-component representations to organize information. Advantages of neural network models:
5. High transparency and interpretability.
6. Ability to use logic and formal rules in systems.
7. Flexibility in modeling various types of information structures.

The use of neural network models is relevant in areas where knowledge formalization, modeling of logical processes, and the creation of information structures are important.

4. Neural Network Information Model of the Brain

Classical deep neural networks have limitations in simulating the brain's informational properties; they simplify neuron dynamics (using perceptrons instead of complex biological neurons). A neural network information model of the brain simulates the brain's multimodal informational functions.

Main neural network approaches:

1. Neuromorphic computing:
 - 1) mimic biological architecture: neurons store and process information simultaneously;
 - 2) use spiking neural networks (SNNs), where data is transmitted in short pulses rather than continuous values;
 - 3) examples: Intel Loihi1 and Loihi2 processors, KapohoBay system.
2. Connectomic models:
 - 1) construct maps of connections between neurons (the connectome) based on neuroimaging data; * analyze network topology, not just node activity;
 - 2) The *Human Connectome* project is an example of large-scale neural connectivity mapping.
 3. Generative and inverse models:
 - 3) recreate the causal mechanisms of perception (e.g., transition from a 2D image to a 3D scene); * example: Tenenbaum's inverse graphical model, which predicts 3D scene parameters from 2D data and is being tested on macaque brain activity.
3. Models based on dynamical systems and information theory:
 - 1) describe brain function through differential equations, attractors, and entropy;
 - 2) focus on global dynamics rather than local neuronal connections.
4. Cognitive architectures:

- 1) Integrate knowledge of psychology, neuroscience, and AI (e.g., SOAR, ACT R);
- 2) Model higher cognitive functions (memory, attention, decision making) without directly copying neural networks.
- 3) Training does not require gradient descent or labeled data.
- 4) The architecture reflects biological organization (layers, clusters, synaptic plasticity).
- 5) The dynamics take into account time delays, spikes, and stochasticity. - Scalability allows for small sets of neurons.
5. Basic Principles and Analogies to the Brain:
 - 1) Hierarchical Information Processing:
 - a) In the brain, information is processed in stages: from simple features (contours, colors) to complex objects (faces, scenes). For example, in the visual system, the ventral stream is responsible for object recognition, and the dorsal stream is responsible for spatial processing.
 - b) Deep neural networks (DNNs) mimic this principle through a multi-layered architecture, where each layer extracts increasingly complex features.
 - 2) Formation of Associations and Abstractions:
 - a) The brain builds dynamic models of the environment, including a hierarchy of generalizations and aggregations.
 - b) Neural networks are capable of learning from data and forming internal representations, for example, in clustering or generation tasks.
 - 3) Learning and Plasticity:
 - a) In the brain, synaptic plasticity (Hebbian rules, long-term potentiation) underlies learning.
 - b) Neural networks use optimization algorithms such as backpropagation, although this mechanism is not considered biorealistic.
6. Examples of neural network models:
 - 1) Convolutional neural networks (CNNs) have been successfully used for visual recognition. Studies have shown that the activity of the final layers of a CNN correlates with the activity of the inferior temporal cortex of primates during image recognition.
 - 2) Transformers, originally developed for language processing, have demonstrated high efficiency in modeling spatial and temporal data. For example, modified transformers are used to simulate the hippocampus, which is key to memory.
 - 3) Spike neural networks aim to reproduce the spiking nature of signal transmission in the brain, which can improve energy efficiency and processing speed.
7. Applications in brain research:
 - 1) Neurophysiological data analysis: Deep learning is used to process MRI, EEG, and other data, helping to identify activity patterns associated with functions or pathologies.

- 2) Modeling cognitive processes: For example, inverse graphical models simulate the perception of 3D scenes from 2D images, consistent with activity in the inferior temporal cortex of macaques.
- 3) Brain-computer interfaces (BCI): Neural networks help interpret brain signals to control external devices.
- 4) Neuromorphic approaches: Aim to create more bio-realistic models using spiking neurons and memory computation.
- 5) Integration with biological data: Projects like the Human Connectome and the Blue Brain Project aim to create detailed maps of neural connections.
- 6) Ethical and philosophical issues: Brain modeling raises issues of privacy, AI liability, and understanding consciousness.

Network-based information models help harness the principles of biological learning and memory; create energy-efficient neuromorphic chips; and develop brain-computer interfaces with better signal interpretability. Full brain simulation remains elusive due to its complexity (86 billion neurons and quadrillions of synapses).

Although neural network models cannot yet fully reproduce the complexity of the human brain, they provide valuable tools for studying its functions and developing new technologies. Further research in neuromorphic engineering and integration with biological data may bring us closer to the creation of more advanced systems that mimic the brain's cognitive abilities [9-15].

5. Informational Multimodal Model of the Brain

The informational multimodal model of the brain describes how the brain integrates and processes multimodal (multi-sensory) signals to form a holistic perception of reality and make decisions. Key principles:

1. Multimodality of perception:

The brain continuously integrates information from different sensory systems (vision, hearing, touch, smell, proprioception, etc.), creating a unified picture of the world. For example, speech perception includes not only sound but also visual cues (lip movements, facial expressions).

2. Hierarchical processing:

Information passes through successive levels of analysis:

- 1) Primary sensory areas (processing basic features: color, tone, texture);
- 2) Association areas (signal synthesis, pattern recognition);
- 3) Prefrontal areas (evaluation, planning, decision making).

3. Predictive coding: The brain generates predictions about incoming signals based on experience. Actual sensory data is compared with these predictions, and discrepancies (prediction errors) are adjusted. This reduces energy expenditure and

speeds up processing.

4. Plasticity and adaptation:

Connections between modalities are dynamically restructured depending on context and learning. For example, in blind people, the visual cortex can process auditory information.

5. Convergence in multimodal areas:

Specific cortical areas (e.g., the parieto-occipital transition area, prefrontal cortex) integrate signals from different modalities. This allows for:

- 1) recognizing objects from different perspectives;
- 2) associating words with images;
- 3) coordinating actions based on multisensory feedback.
- 4) Modern multimodal maps (e.g., a 2016 study from the University of Washington) combine:
- 5) structural data (high-resolution MRI);
- 6) functional connectivity (fMRI); - myelination and neuronal density.
- 7) 180 color-coded areas by modality (vision - blue, hearing - red, touch - green).
- 8) The somato-cognitive action network (SCAN) is an example of the integration of motor and cognitive functions in the cortex, where areas responsible for movement alternate with planning areas.
- 9) Neurorehabilitation: using multimodal stimulation (e.g., combining visual and tactile signals) to restore function after injury.
- 10) Brain-computer interfaces (BCI): taking into account multimodal activity patterns for more precise control of prosthetics or virtual environments.
- 11) Artificial intelligence: inspiration for creating multimodal AI systems that simulate the integration of sensory data.

6. Multimodal neural networks are artificial intelligence models capable of processing and integrating data from different sources (text, images, audio, video, etc.). They mimic the way the human brain perceives the world by combining information from various sensory channels. Such networks are used in various fields, including medicine, robotics, and corporate communications. 7. Brain-machine interfaces (BMIs) are technologies that enable two-way communication between biological neural systems and digital devices. They can analyze the brain's electrical activity (for example, using EEG) and convert it into digital data. Multimodal BMIs can combine multiple types of data, such as EEG and visual stimuli, to improve classification and analysis.

8. Brain theories inspired by multimodal models – some researchers compare brain function to multimodal neural networks. For example, predictive coding theory describes the brain as a system that constantly creates internal models of the world and adjusts them based on sensory data.

Thus, the multimodal model emphasizes that the brain is not a set of isolated modules, but a flexible network where the integration of heterogeneous information underlies cognition and adaptation.

6. Conclusion

AGI (artificial general intelligence) developers are using brain models as information processing mechanisms. Neuromorphic computing, computational neuroscience, and multimodal integration link different types of information. The Human Brain Project integrates the creation of multiscale brain models. Brain models learn from small data sets and generalize from experience, which is one of the goals of AGI. Brain models serve as a tool for AGI to achieve the status of artificial consciousness in processing multimodal information. Intelligent brain models and AGI are becoming assistants to humanity in solving scientific and practical problems.

The author proposed a Mega Project for solving scientific and practical problems using an axiomatic coaching AGI solver method on a brain-like neural network:

Stage 1. Creating a brain-like neural network:

- 1) Developing a brain-like spiking neural network project using modern technologie.
- 2) Implementing a brain-like spiking neural network project on neuromorphic chips.

Stage 2. Creating a neural network-based axiomatic coaching AGI solver system:

- 1) Developing a neural network-based axiomatic coaching AGI solver system.
- 2) Software implementation of a neural network-based axiomatic coaching AGI solver system.
- 3) Debugging an axiomatic system to build a system of axioms for solving problems based on their formulations.
- 4) Debugging an axiomatic system to build knowledge and skills for solving problems based on their formulations and axioms.
- 5) Debugging the coaching system to determine the conditions for solving problems based on their formulations.
- 6) Debugging the solver system to generate solutions to problems, as well as to generate messages about the impossibility of solving problems within the given knowledge system and current conditions.

Stage 3. Testing the neural network axiomatic coaching solver AGI system on a brain-like spiking neural network with formulations of scientific and practical problems, generating solutions or messages about the impossibility of solutions within the given knowledge system and current conditions.

The neural network axiomatic solver coaching method is proposed for implementation as artificial 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.

Automated analytics using brain models, based on big data and artificial intelligence, the results obtained, and the decisions made by the neural network coaching solver AGI system, improves artificial consciousness to solve more complex problems.

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 on an ethical basis (Luke 6: 48).

Abbreviations

ETL	Extract Transform Load
CNN	Cable News Network
RNN	Recurrent Neural Network
NLP	Natural Language Processing
CV	Computer Vision
IoT	Internet of Things
SQL	Structured Query Language
GDPR	General Data Protection Regulation
ML	Machine Learning
AI	Artificial Intelligence
KPI	Key Performance Indicators
MVP	Minimum Viable Product
SNN	Spiking Neural Networks
MRI	Magnetic Resonance Imaging
EEG	Electroencephalography
fMRI	Functional Magnetic Resonance Imaging
SCAN	Somato-cognitive Action Network
BCI	Brain-computer Interfaces
AGI	Artificial General Intelligence

Author Contributions

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

Conflicts of Interest

The author declares no conflicts of interest.

References

- [1] Gregory Dane Clemenson & other. Exploring the Spatial Relationships Between Real and Virtual Experiences: What Transfers and What Doesn't. *Front. Virtual Real.*, 08 October 2020.
- [2] Olatayo, T. O. & Ekerikevwe K. I. (2022) Performance Measures for Evaluating the Accuracy of Time Series Hybrid Model Using High Frequency Data. *Vol 4 No 3: Britain International of Exact Sciences Journal*, September. pp. 244-259.

- [3] Yushan Li, Shu Zhang & Xinyi Zhang. Architectural AI Design Based on Fused Text and Image Data in the Context of a Carbon-Silicon World. *Journal of Research in Social Science and Humanities*, Vol 2, No 9 (2023). pp. 44-50.
- [4] Alan D. Duncan. Over 100 Data and Analytics Predictions Through 2025. *Gartner, Inc. | G00744238*. 2025. 1-28.
- [5] Simplilearn. Top Data Science Trends Reshaping the Industry in 2025. *Data Science & Business Analytics*. 2025. <https://www.simplilearn.com/data-science-trends-article>
- [6] Jeffrey Richman. 9 AI trends that will revolutionize data science in 2025. *Data Science*. 2025. <https://estuary.dev/blog/ai-trends/>
- [7] Evgeny Bryndin. Neural Network Axiomatic Solver Coaching AGI Method for Solving Scientific and Practical Problems. *American Journal of Mathematical and Computer Modelling*. 2025, Vol. 10, No. 4, pp. 110-120. <https://doi.org/10.11648/j.ajmcm.20251004.11>
- [8] Evgeny Bryndin. Implementation of AGI on Brain-Like Neuro-Network Structure. *Software Engineering*. Volume 11, Number 3, 2025. *In press*.
- [9] Evgeny Bryndin. Creation of Multi-purpose Intelligent Multimodal Self-Organizing Safe Robotic Ensembles Agents with AGI and cognitive control. *COJ Robotics & Artificial Intelligence (COJRA)*. Vol. 3, Issue 5. 2024. pp. 1-10.
- [10] Evgeny Bryndin. Creation of Multimodal Digital Twins with Reflexive AGI Multilogic and Multisensory. *Research on Intelligent Manufacturing and Assembly*. Vol. 2, Is. 1. 2024. pp. 85-93.
- [11] Evgeny Bryndin. Formation of Motivated Adaptive Artificial Intelligence for Digital Generation of Information and Technological Actions. *Research on Intelligent Manufacturing and Assembly*. V. 4, Is. 1. 2025. pp. 192-199. <https://doi.org/10.25082/RIMA.2025.01.006>
- [12] Evgeny Bryndin. Theoretical Foundations of Neural Network Integration of System Software Modules. *Software Engineering*. 2025, Vol. 11, No. 2, pp. 30-39. <https://doi.org/10.11648/j.se.20251102.11>
- [13] Evgeny Bryndin. Self-learning AI in Educational Research and Other Fields. *Research on Intelligent Manufacturing and Assembly*. V. 3, Issue 1. 2025. pp. 129-137.
- [14] Evgeny Bryndin. Technological Stages of Neural Network AI Generation of System Program Code Based on Modular Neuro Integration. *American Journal of Embedded Systems and Applications*. 2025, Vol. 10, No. 1, pp. 17-23. <https://doi.org/10.11648/j.ajes.20251001.12>
- [15] Evgeny Bryndin. From Creating Virtual Cells with AI and Spatial AI to Smart Information Multi-Level Model of the Universe. *Journal of Progress in Engineering and Physical Science*, V. 4, Is. 1. 2025. pp. 1-7.