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ARTIFICIAL BRAIN. BIOLOGICAL AND ARTIFICIAL NEURAL NETWORKS, ADVANTAGES, DISADVANTAGES, AND PROSPECTS FOR DEVELOPMENT

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Анотація. У статті аналізується проблема розвитку штучних нейронних мереж у рамках розробки штучного мозку. Розглядаються структура та функції біологічного мозку. Мозок виконує безліч функцій, таких як контроль роботи організму, координації рухів, обробки інформації, пам'ять, мислення, увага, регулювання емоційного стану і складається з мільярдів нейронів, об'єднаних безліччю зв'язків у біологічну нейронну мережу. У роботі обговорюються структура та функції біологічних нейронних мереж, докладно описуються переваги та недоліки порівняно зі штучними нейронними мережами. Біологічні нейронні мережі вирішують різні складні завдання в реальному часі, які і досі недоступні для штучних мереж, наприклад, одночасне сприйняття інформації з різних джерел, включаючи зір, слух, нюх, смак та дотик, розпізнавання та аналіз сигналів зовнішнього середовища з одночасним прийняттям рішень у відомих та невизначених ситуаціях. У цілому, незважаючи на всі переваги біологічних нейронних мереж, штучний інтелект продовжує швидко прогресувати та поступово відвойовувати позиції у біологічного мозку. Передбачається, що в майбутньому штучні нейронні мережі зможуть наблизитись до можливостей людського мозку і навіть перевершити його. Проводиться порівняння нейронних мереж головного мозку людини із штучними нейронними мережами. Описуються глибинні нейронні мережі, їх навчання та використання у різних додатках, докладно обговорюються їхні переваги та недоліки. Аналізуються можливі шляхи подальшого розвитку цього напрямку. Коротко розглядаються проєкт «Human Brain», спрямований на створення комп'ютерної моделі, що імітує функції людського мозку, та проєкт просунутого штучного інтелекту – ChatGPT. Для розробки штучного мозку пропонується новий тип нейронних мереж – нейроподібні мережі, структура і функції яких аналогічні природним біологічним мережам. Наводиться спрощена схема структури штучного мозку на базі нейроподібної мережі.

Ключові слова: штучний мозок, біологічні нейронні мережі, штучні нейронні мережі, нейроподібні зростаючі мережі.

Abstract. The article analyzes the problem of developing artificial neural networks within the framework of creating an artificial brain. The structure and functions of the biological brain are considered. The brain performs many functions such as controlling the organism, coordinating movements, processing information, memory, thinking, attention, and regulating emotional states, and consists of billions of neurons interconnected by a multitude of connections in a biological neural network. The structure and functions of biological neural networks are discussed, and their advantages and disadvantages are described in detail compared to artificial neural networks. Biological neural networks solve various complex tasks in real-time, which are still inaccessible to artificial networks, such as simultaneous perception of information from different sources, including vision, hearing, smell, taste, and touch, recognition and analysis of signals from the environment with simultaneous decision-making in known and uncertain situations. Overall, despite all the advantages of biological neural networks, artificial intelligence continues to rapidly progress and gradually win positions over the biological brain. It is assumed that in the future, artificial neural networks will be able to approach the capabilities of the human brain and even surpass it. The comparison of human brain neural networks with artificial neural networks is carried out. Deep neural networks, their training and use in various applications are described, and their advantages and disadvantages are discussed in detail. Possible ways for further development of this direction are analyzed. The

Human Brain project aimed at creating a computer model that imitates the functions of the human brain and the advanced artificial intelligence project – ChatGPT – are briefly considered. To develop an artificial brain, a new type of neural network is proposed – neural-like growing networks, the structure and functions of which are similar to natural biological networks. A simplified scheme of the structure of an artificial brain based on a neural-like growing network is presented in the paper.

Keywords: artificial brain, biological neural networks, artificial neural networks, neural-like growing networks.

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1. Introduction

In the world of computer technology, neural networks are the most promising direction for the development of artificial intelligence. This technology is one of the fastest-growing areas of artificial intelligence, which has tremendous potential in solving various tasks, ranging from image processing and speech recognition to creating autonomous robots and intelligent technical assistants. However, despite significant advancements in this field, computer neural networks have a number of significant differences from biological neural networks that operate in the human brain. Biological and artificial neural networks are multi-component systems capable of perceiving, processing, and analyzing information. Biological neural networks are the basis for the functioning of the biological brain, while artificial neural networks are models of this process using computer algorithms.

The aim of the article is to analyze the differences between biological and artificial neural networks, to examine the functioning and application of the most popular deep neural networks currently in use, to analyze existing ways to improve artificial neural networks, and to provide a brief description of the application.

2. The biological brain

The brain is an organ of the nervous system that controls the body's functions and provides for higher mental functions such as memory, speech, thinking, and attention. The brain processes information from all sensory systems, controls and coordinates movements, and regulates emotional states and intellectual activity.

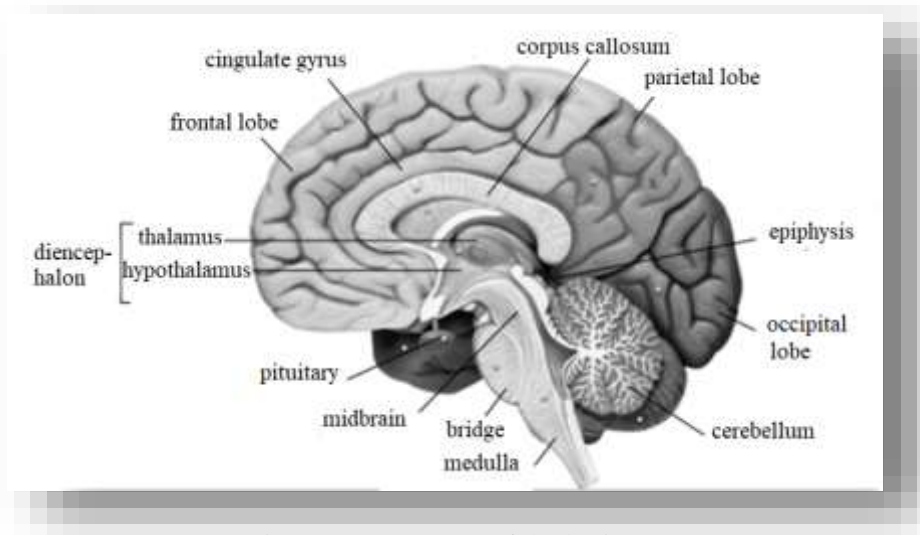


Figure 1 – Structure of the brain

Traditionally, the brain is divided into five main parts: the medulla oblongata and pons, the cerebellum, the midbrain, the diencephalon, and the cerebrum (Fig. 1). The medulla oblon-

gata and pons are the key structures in organizing basic life functions such as breathing, heart rate, and blood pressure. The reticular formation, located along the medulla oblongata and pons, controls behavior, movement, sensory and endocrine systems, as well as sleeping and wakefulness. The cerebellum is the center for motor learning and motor memory, coordinating movements and their automation. The midbrain filters and identifies visual and auditory signals and

activates orienting and/or defensive reflexes in response to new and significant signals. The limbic system plays an important role in regulating internal organ function, emotional control, memory, sleeping, and wakefulness. It includes several structures such as the cingulate gyrus, hippocampus, amygdala, thalamus, and hypothalamus. The cingulate gyrus provides for the switching of attention between tasks that the brain solves. The hippocampus is a key element in the formation of memory mechanisms. The amygdala controls emotional reactions and behavior. The thalamus can be compared to the main controller of our body, gathering information from our organs and sensory systems and making decisions about the transmission of this information to decision-making centers in the cerebral hemispheres to regulate behavior.

2.1. Cortex of the cerebral hemispheres

The cortex of the cerebral hemispheres performs complex information processing, decision-making, and behavior programming. It consists of 10^{10} neurons, and each neuron has up to 10,000 connections with neighboring cells, ensuring flexibility and reliability in cortical functions. It is divided into five regions, each specializing in a specific function. The occipital lobe is primarily responsible for visual information processing, while the temporal lobe is involved in auditory processing. The parietal lobe comprises the somatosensory and associative cortex. The somatosensory cortex collects and accumulates signals from sensory systems, while the associative cortex forms the language representation of the world. The prefrontal cortex includes the associative frontal lobe and the motor cortex. The associative frontal lobe is the center for making rational decisions such as planning, forecasting, and focusing attention. The motor cortex is responsible for executing complex movements (Fig. 1). The cortex is composed of neuronal columns which are the basic functional units. The columns consist of vertically arranged pyramidal and stellate neurons connected by horizontal connections, forming neuronal ensembles. They traverse six horizontal layers of the cortex and are responsible for information processing (Fig. 2).

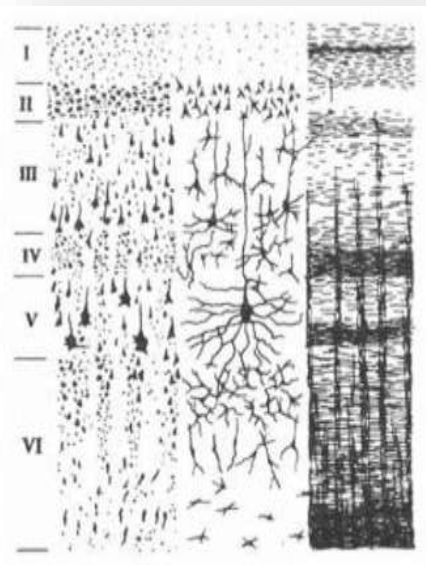


Figure 2 – Columns of the cerebral cortex

Large pyramidal neurons are located in the center of the columns and form their foundation. They are considered responsible for the overall response of the column. Above them, there are smaller cells with dendrites known as the crown. Within the crown, connections form a unique memory of the column. Information coming to the brain passes through the lower layers of the cortex where the simplest properties of objects are identified such as lines, colors, and sound intensity. Cells that detect lines or edges at specific angles are highly activated here. This edge can be a part of any object such as a part of an item or a side of a letter. Neurons located higher up gather information from the simple neurons, refine, and generalize the received signal within the column. For example, these neurons are not only concerned with the contrast and tilt of a stripe but also its length. Information processed in the lower layer moves to the upper layer where it becomes increasingly generalized.

Some parts of it are discarded, and ultimately, we obtain a holistic image. Minicolumns combine to form hypercolumns which are even larger structures. Hypercolumns also interact with each other through horizontal connections, allowing for more complex and comprehensive information processing. In addition, hypercolumns can process information from different parts of the cortex and integrate it, allowing for the creation of a coherent perception of the

world. Simple neurons in the visual cortex serve as detectors of elementary stimulus features. For example, they respond to the contrast of linear stimuli such as stripes or edges between light and dark surfaces, with different sensitivity to the angle of the line's tilt. Several simple neurons converge onto a complex neuron that responds to the stimulus later than the simple cells. The receptive field of complex neurons consists of multiple small receptive fields of simple neurons, and the effective stimulus for complex neurons becomes the character and direction of the stimulus movement through the receptive field rather than just its orientation. This allows for the transition from the detection of simple signals to their abstraction and generalization. Interneurons within the local network of the cortical column participate in this process, and the outcome of the transformation is the level of activity of output neurons that leave the column to interact with other columns. Each cortical column represents a functional unit of the cortex called a micromodule.

The cerebral cortex contains various areas, including sensory, motor, and associative ones, each of which plays an important role in information processing and the control of bodily functions. Sensory areas analyze incoming information from receptors, motor areas send commands to the working organs, and associative areas connect motor and sensory areas and store information related to learning, speech, thinking, and consciousness. Consciousness is a complex and highly organized process that allows humans to be aware of their existence, perceive the surrounding world, think, feel, understand, and analyze what happens within and around them. Various concepts associated with consciousness such as attention, perception, memory, thinking, speech, and others help us navigate the environment, interact with other people, and perform various actions. Moreover, consciousness possesses qualitative characteristics such as individuality, uniqueness, and free will. Despite years of research in the field of neuroscience, scientists have not yet been able to fully explain how consciousness arises in the human brain and how it is related to biological processes.

2.2. The reflexive nature of higher brain activity

The assumption of the reflexive nature of higher brain activity was first developed by the physiologist I.M. Sechenov. His ideas were further developed in the works of I.P. Pavlov who discovered ways of objective experimental investigation of cortical functions, developed the method of conditioned reflex formation, and created the doctrine of higher nervous activity. The functioning of the nervous system is based on reflexes. A reflex is a responsive reaction of an organism to changes in the internal and external environment, carried out with the involvement of the central nervous system.

According to the teachings of I.P. Pavlov, reflexes are divided into two groups: unconditional reflexes carried out through innate, genetically determined neural pathways, and conditional reflexes mediated by neural connections formed during an individual's life. Unconditional reflexes emerge from birth and are inherited. They help to ensure survival in the early stages of development. Conditional reflexes are acquired throughout life. They can be formed in response to natural stimuli (such as the smell or sight of food) as well as artificial stimuli (such as light or changes in temperature).

The reflex arc is considered the basis of any reflex. The reflex arc is the pathway through which the stimulus (signal) from the receptor travels to the effector organ.

The structural basis of the reflex arc consists of neuronal chains composed of sensory neurons (2), interneurons (3), and motor neurons (4). It is these neurons and their processes that form the pathway through which nerve impulses from the receptor (1) are transmitted to the effector organ (5) during the execution of any reflex (Fig. 3).

Unconditional reflexes are innate and do not depend on experience. They are elicited by stimuli from the external or internal environment such as light, sound, pain, or other forms of irritation. The structural organization of neurons responsible for unconditional reflexes consists of three main elements: receptors, sensory neurons, and effectors. Receptors are located in various

parts of the body and are specialized cells that respond to different types of stimuli. Effectors are also specialized cells that are responsible for carrying out the response to the stimulus. Effectors can be muscles that contract in response to the stimulus or glands that release hormones in response to the stimulus.

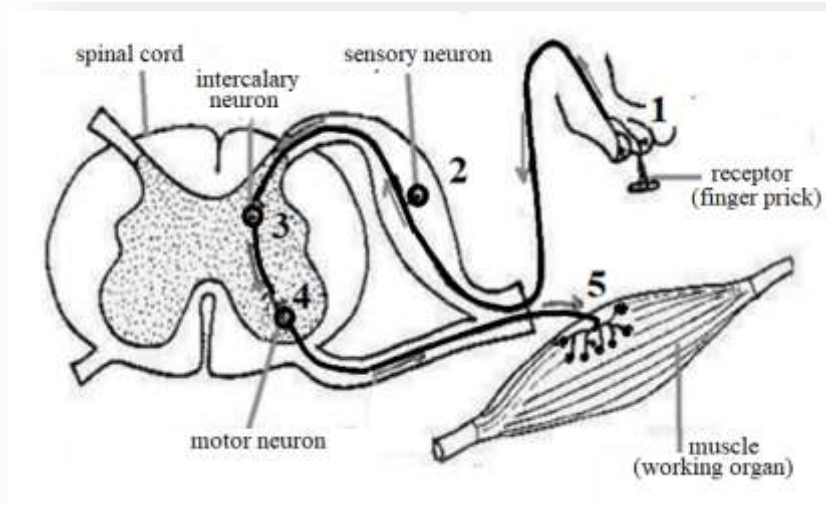


Figure 3 – Reflex arc

In the case of conditional reflexes, the organism's response to the stimulus depends on its previous experience. Such reflexes arise as a result of learning and can be modified over time. The structural organization of neurons responsible for conditional reflexes also includes receptors, sensory neurons, and effectors. However, in this case,

the brain plays a more significant role in signal processing and generating a response. Conditional reflexes are associated with specific areas of the brain that process and analyze information. When sensory neurons transmit a signal to the brain, it is analyzed and linked to previous experiences that the organism has had. The brain then forms a response based on this experience and transmits it to the effectors for execution.

Thus, the brain is a complex organ composed of billions of neurons that are interconnected in a biological neural network.

3. Biological neural networks

A biological neural network refers to the billions of nerve cells (neurons) in the brain of living organisms that process information received from sensory systems and control the organism's behavior.

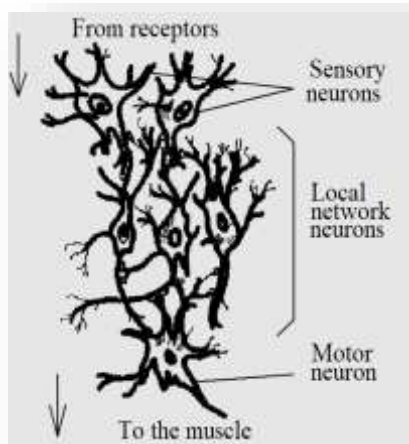


Figure 4 – Neurons of functional blocks

Neurons in the brain communicate with each other, and their efficiency depends on the quantity and quality of connections between them. Neural connections are constantly forming, rearranging, and breaking apart, depending on the information received by the organism and how it is utilized. The brain can be divided into three main functional blocks: the sensory analysis block responsible for receiving and processing sensory information, the limbic-reticular systems block involved in modulating and activating the nervous system, and the motor analyzer block responsible for programming, initiating, and controlling behavior. These blocks interact with each other.

Sensory neurons form the first level of the hierarchy and transmit signals to neurons in the local network where signal processing takes place. The nature of signal processing in the local networks determines the excitation of motor neurons that control the organism's behavior (Fig. 4). Local neurons

(modeling systems) make decisions about which type of behavior should be initiated and transmit this information through motor neurons to muscle tissue cells.

Biological neural networks have several advantages over artificial ones. These are the ability to perform various tasks, simultaneous perception and processing of information from different sources, and real-time learning and adaptation to new conditions. The biological brain possesses a wide range of data acquired through years of experience, learning, and adaptation to the environment, while most artificial neural networks are trained on a limited dataset that limits their ability to make right decisions in non-standard situations. However, artificial intelligence is rapidly evolving and improving. The creation of the virtual robot ChatGPT is evidence of significant progress in the field of artificial intelligence. ChatGPT is a product of complex technological development that involved deep learning methods using vast databases. This enabled it to learn to communicate with humans in natural language and perform tasks related to information retrieval, data analysis, and query processing. The creation of such a robot has enormous potential for automating communications in various fields from customer service to education and medicine.

The development of advanced AI models like ChatGPT gives hope to AI researchers that in the future, it will be able to approximate and even surpass the capabilities of the human brain. This can be achieved through the development of new algorithms, hardware improvements, and more accurate modeling of biological neural networks.

4. Artificial neural networks

Neural networks are algorithms that model the functioning of the nervous systems of animals and humans. However, there are significant differences between artificial and biological neural networks.

Biological neural networks have a decentralized, multidimensional, block-like, and multi-layered architecture, whereas artificial neural networks typically have a centralized, single- or multi-layer architecture that only approximates the biological neural network. In biological neural networks, functions are distributed, and each neuron performs multiple tasks. In artificial neural networks, functions are distributed among neurons, each of which performs only one function. Biological neural networks learn through experience and interaction with the environment, while artificial neural networks are trained based on training datasets consisting of large amounts of labeled examples.

Biological neural networks can quickly solve various tasks even with limited input information. Artificial neural networks can be highly performant but they require large amounts of data to solve tasks. Additionally, biological neural networks efficiently utilize energy and do not require significant computational resources, unlike artificial neural networks that demand substantial computational power.

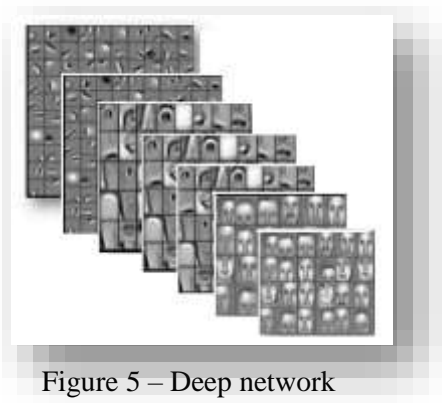


Figure 5 – Deep network

4.1. Deep neural networks

Deep neural networks (DNNs) are an advanced machine learning method that relies on the use of artificial neural networks with multiple hidden layers (Fig. 5).

Each hidden layer contains numerous neurons that take input data and perform calculations on the weights of connections between the neurons before passing the result to the next layer. DNNs allow for solving complex tasks such as image recognition, text analysis, and speech processing, and can also be used in autonomous systems and other domains. The training process of DNNs involves passing input data through the layers of

the network and mathematical transformations that determine the importance of each input signal. The output of the network yields a result that can be used to solve the task at hand. The use of multi-layer architectures enables the extraction of distinctive features from the input data, making deep learning highly effective. In most cases, convolutional neural networks (CNNs) are used for implementing deep learning as they enable the automatic extraction of features from images and the processing of sequential data such as audio signals and speech. CNNs consist of layers where nodes in each layer are grouped into clusters that can overlap, and each cluster passes data to multiple nodes in the next layer. This architecture makes deep learning unique as the machine itself discovers features – key characteristics of something that make it easier to distinguish one class of objects from another one – and organizes features hierarchically, where simpler features are combined to form more complex ones.

One of the most popular methods for training deep neural networks is backpropagation. At the beginning of the training process, the network's weights are initialized with random values. Then, the network goes through a training dataset, and on each iteration, the error between the network's output and the target values is calculated. After that, the error is propagated backward through the network from the output layer to the input one. The weights are adjusted based on the error magnitude, and the process is repeated until the error reaches a predefined threshold. This way, the network is tuned to minimize prediction errors. Once the network is trained, it can be used for classification. When an input image is presented, the neurons in the first layer scan the image, getting activated in the regions that correspond to specific features of the image. Then, the network analyzes increasingly complex combinations of these basic features and ultimately makes a conclusion about the class the image likely belongs to. In this way, deep neural networks automatically extract features from complex data and utilize them for classification and prediction.

Deep learning is a powerful method of machine learning. Yann LeCun, the Chief AI Scientist at Facebook AI Research, states that “Deep neural networks are a true breakthrough in the field of artificial intelligence. They have the ability to extract complex hierarchical features from data, which makes them particularly powerful tools for solving a wide range of machine learning tasks [1].” Jürgen Schmidhuber, the director of the Institute of Artificial Intelligence, says that “Deep neural networks have tremendous potential for solving tasks that were considered unsolvable until recently. They can discover intricate dependencies in data and learn from large datasets using parallel computations [2].” Geoffrey Hinton, one of the pioneers of deep learning, believes that “Deep learning is like magic. It can create systems that go beyond our understanding, yet they work and achieve incredible results [3].”

On the other hand, training and utilizing deep neural networks is a resource-intensive process that requires a large amount of data and computational resources. Preparing training datasets for deep neural networks is a mandatory and highly important procedure that can significantly impact the model's performance. Andrew Ng, one of the most renowned experts in deep learning, states that “80% of the time spent on developing deep models is devoted to data preparation [4].” Fei-Fei Li, a professor of computer science at Stanford University, says that “data preparation is the most critical step when working with deep learning [5].” Yoshua Bengio, one of the founders of deep learning, asserts that “data quality is the primary factor determining the success of deep learning [6].”

In their article titled Large Scale Distributed Deep Networks, Jeff Dean and others describe the application of distributed deep neural networks in real-world applications such as speech recognition, natural language processing, and computer vision. They address the problem of training deep networks with billions of parameters [7]. Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton describe the training of deep neural networks for image classification using the ImageNet dataset which contains 1.2 million images. For this task, the authors used a neural network with 60 million parameters and 650,000 neurons consisting of five convolutional layers,

some of which are accompanied by max-pooling layers and three fully connected layers with a final 1000-way softmax. To speed up training, a highly efficient implementation of the convolution operation on GPUs was used [8].

Indeed, training deep neural networks requires significant computational power and a long training time. To address this problem, several approaches are employed. These are ready-to-use machine learning libraries that provide a simple interface and automatically optimize computations, cloud computing that allows renting computational resources on remote servers to perform computations in a cloud environment, and network pruning techniques that reduce the number of parameters and accelerate training. Additionally, research is being conducted to discover new methods for optimizing computations in deep neural networks.

4.2. Improving artificial neural networks

To improve artificial neural networks and make their operation closer to biological neural networks, researchers propose several approaches.

One such approach is the development of new neural network learning algorithms that resemble the learning processes in biological neural networks. For example, in biological neural networks, continuous learning occurs, where each new experience influences the modification of connections between neurons. This is different from most artificial neural network training algorithms, where training occurs by presenting a set of data, after which the weights of connections between the neurons are adjusted in accordance with the given algorithm.

The second way is to use new types of hardware that can process large amounts of data more efficiently. One of these types is neuromorphic chips developed under the influence of biological principles and can process information in an analog way that is more consistent with the work of biological neural networks.

There is also the idea of creating hybrid systems that combine the advantages of artificial and biological neural networks. Such systems can be applied in various fields, for example, in medicine to create bionic prostheses or in automatic transport control. For instance, autonomous cars can use artificial neural networks for object recognition and decision-making, as well as biological neural networks (such as the driver's brain) to make more complex decisions based on experience and intuition. This approach can significantly improve the safety and efficiency of automatic transport control. Tesla has released its own chip for self-driving cars. The Tesla FSDC Onboard Processor for Autonomous Vehicles is characterized by the high performance of the built-in neural accelerator with relatively low power consumption. The chip is compatible with Tesla's current fleet of electric vehicles. According to Tesla CEO Elon Musk, who presented the innovation at the Autonomy Day conference, this is "the best chip in the world". Founded by Elon Musk, Neuralink is developing a technology that links the human brain and the computer. The goal of Neuralink is to create an interface that will allow people to control computers and other devices directly with their thoughts. This emerging technology makes it possible to create a connection between a living brain and a computer network and to transfer various information in both directions. First of all, it will let people simplify the process of restoring various hearing and vision disorders. According to Musk, this technology will help the paralyzed to walk, the blind to see, and other people just heal from other injuries and communicate with artificial intelligence on their own.

However, there is also a theory about the possibility of controlling specific areas of the brain and transmitting data from them. To some extent, this can be useful in solving certain medical problems but may raise concerns about privacy and personal integrity. If the technology is used in accordance with ethical and legal norms, it can bring great benefits to the field of medicine and public welfare. Overall, the development of hybrid systems is a promising direction for the advancement of neural networks. However, implementing such systems requires significant effort and experimentation, as well as the integration of interdisciplinary knowledge and technol-

ogies. In the future, we can expect even closer integration between artificial and biological systems, which, in turn, will lead to further discoveries and technological breakthroughs in various fields.

But despite the fact that artificial neural networks are considered a counterpart to biological neural networks, the biological brain does not function in the same way. There is no need for the brain to compute the outputs of every single one of its 100 billion neurons for any action, it only activates the parts that are actually necessary for a specific task. Similarly, when we learn a new word, it doesn't mean that the “weights” of trillions of synapses will be updated.

A third approach is to create neural network architectures that more accurately model the anatomy and functioning of biological neural networks. Some researchers propose using multi-layer neural networks that mimic the brain's structure, where each layer represents a specific layer of brain neurons, resembling a biological neural network.

In this work, for creating an artificial brain, neural-like growing networks with a structure and functioning similar to natural biological networks are offered. Despite the vast number of developed and utilized classes of neural networks, neural-like growing networks represent a new type of neural network with no analog.

5. Neural-like growing networks

A neural-like growing network (n-GN) is a collection of interconnected neural-like elements (neurons) designed to receive, analyze, and transform information during the interaction with objects in the real world, similarly to the biological nervous system. The number of connections entering a neural-like element is equal to the number of features characterizing the input information (e.g., color, size, shape, etc.), and each connection coming into a neural-like element is assigned a weight coefficient that represents the significance of that feature (e.g., the strength of touch, sound intensity, brightness, etc.). Each neural-like element is assigned a certain activation threshold. During the reception and processing of information, the network changes its structure.

N-GNs are described as directed graphs where neural-like elements are represented as vertices and the connections between elements are represented as edges. Thus, the network represents a parallel dynamic system with the topology of a directed graph that processes information by changing its state and structure in response to external stimuli. In the theory of multi-connected neural-like growing networks, the main concepts are the concepts of structure and architecture that reveal the scheme of connections and interactions between the network elements. The topological (spatial) structure is the directed graph of connections between the network elements, and the logical structure defines the principles and rules for forming connections and elements of the network, as well as the logic of its functioning. The network architecture is determined by the scheme of connections between the physical elements of the network, the rules for forming connections and elements, as well as the logic of its functioning) [9].

Neural-like growing networks are a new type of neural networks that include the following classes: multiply connected (receptor) neural-like growing networks (mn-GN); multi-connected (receptor) multidimensional neural-like growing networks (mmn-GN); multiply connected receptor-effector neuron-like growing networks (mren-GN); multiply connected multidimensional receptor-effector neural-like growing networks (mmren-GN) [10–14].

5.1. Multidimensional receptor-effector neural-like growing networks

Multi-connected multidimensional receptor-effector neural-like growing networks are the basic structure of artificial brain systems and are similar to the neural networks of the human brain. Mmren-GN is a homogeneous structure in which by modeling the basic law of biology – the unity of the organism and the environment – carried out on the basis of the unconditional reflex ac-

tivity of the nervous system, knowledge, forms of behavior, and performance of actions are acquired and accumulated in accordance with environmental conditions.

As is known, the processes that occur in the nervous system are divided into three main types: sensory, integration – the interpretation of information received from sensory cells, and motor. The sensory process occurs when our senses such as sight or touch receive information

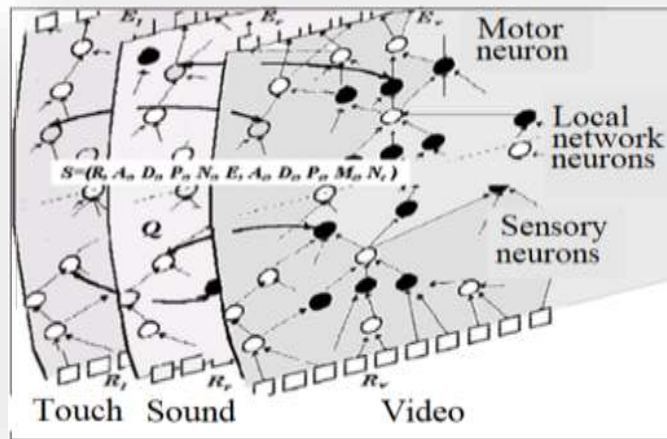


Figure 6 –Topological structure of mmren-GN

from the environment. Nerve cells, or neurons, transfer this message directly to the brain.

In mmren-GN, the processes of perception, integration, and movement are formed in the structure of a neural network. Information about the external world, its objects, their states and situations that describe the relationship between them, as well as information about the actions caused by these states, is stored due to its reflection in the network structure. At the same time,

the arrival of new information causes the activity of new associative vertices and connections and their redistribution between the vertices that have arisen earlier, while the common parts of these descriptions and actions are highlighted, which are automatically generalized and classified, and the information is simultaneously described and analyzed in various dimensions, for example, visual, sound, tactile, etc. (Fig. 6) [9,15].

6. Artificial brain

The development of an artificial brain (AB) is a field of research that aims to create computer systems capable of modeling the functions of the human brain. This area of science and technology is multidimensional and encompasses various approaches and methods.

One of the most well-known projects in the field of neuroscience and artificial intelligence is the Human Brain Project. Launched in 2013 by the European Union, it has brought scientists and engineers together from around the world. The goal of the Human Brain Project is to create a computer model that accurately simulates the functions of the human brain. This model should include millions of neurons and the connections between them that facilitate information exchange in the brain. The Human Brain Project is currently under development. Overall, it continues to attract the attention of scientists and the general public due to its ambition and potential significance for science.

Another approach to developing artificial intelligence similar to humans is the use of deep neural networks. Using this approach, OpenAI has created ChatGPT. It has garnered significant attention from millions of users due to its exceptional capabilities, enabling productive conversations, generating stories and articles, writing code, and even finding errors in it. GPT-4 is a multimodal model that can work with text, sound, and images, opening up new possibilities for users and challenges for developers. Additionally, ChatGPT can understand natural language and perform tasks in different languages, assisting people in various fields from marketing to solving school problems. ChatGPT processes information using a set of words and their probabilities of combination. It has access to a vast database for analysis, predictions, and problem-solving but lacks emotions and feelings. However, if we did not know how ChatGPT works, then when evaluating its intelligence within the framework of the Turing test, we might consider it to have intel-

ligence and even a sense of humor. At the very least, it understands what humor is, as evidenced by the conversation below between ChatGPT and a person.

Person: *Can you come up with something witty on any topic, say, some witticisms?*

ChatGPT: *Certainly, I can. Wit is like spices in a dish. If you add too much, the dish can become inedible, but if you add them in moderation, they give it a special taste and aroma. Similarly, wit can be wonderful if used wisely and at the right moments. However, if you overdo it, you may end up with an unpleasant outcome.*

Person: *Give me a few examples of witticisms.*

ChatGPT: *Of course, here are a few examples of witticisms that can be used in different contexts:*

"This humor is so old that you can find it in the natural history museum."

"Your idea is so original that even Instagram hasn't copied it yet."

"This pie is so dry that even sand in the desert feels more moisturized."

"You're so smart that you could explain quantum physics in a kindergarten."

"You're so fast that you could outrun a duck on a bicycle."

But it's important to remember that witticisms should be used with caution to avoid hurting or offending others.

Understanding how ChatGPT works, we realize that it conducts this conversation based on the knowledge it was trained on, i.e. data uploaded to it by its creators. Unfortunately, it cannot feel emotions, think creatively, or have its own beliefs and opinions. It lacks sensory organs and cannot create its own experiences or knowledge. Unlike the human brain which constantly updates its information stores based on new data, ChatGPT only uses the data it has been given. The results obtained from it are based on a probabilistic assessment of the available data. While ChatGPT is an impressive technological achievement, it cannot replace the human brain. Over 70 years ago, Alan Turing warned that programming a machine to draw conclusions from large data sets is insufficient to create a machine capable of thinking. For artificial intelligence to truly deserve its name, it must be capable of inductive reasoning, i.e. the ability to go from specific instances to broader principles.

Some experts consider the emergence of GPT-4 "a turning point in the industry". On the other hand, considering the limitations of deep neural networks, some experts believe that there is a need for the development of fundamentally new approaches to address the differences between the functioning of biological and artificial neural networks. It is necessary to develop radically new technologies that will improve the performance of artificial neural networks, bringing them closer to their biological counterparts. This will enable the use of these technologies in creating more advanced human-like robots and intelligent systems. There are various research directions in the field of artificial intelligence such as the development of deep learning algorithms and the creation of new machine learning methods that will enhance the functionality and accuracy of neural networks.

However, mmren-GN is a new, unparalleled in the environment of artificial neural networks, far-reaching and promising technology for creating an artificial brain for humanoid robots and intelligent systems. A simplified diagram of the structure of the artificial brain on mmren-GN is shown in Fig. 7.

The artificial brain is a multidimensional structure consisting of areas of a neural network responsible for processing visual information, sound, tactile, etc. In each area, sensitive, associative, and motor zones are distinguished. The sensitive area consists of receptors and sensory neurons (neural-like elements). The association zone is a set of local neurons that make up the thalamus-hypothalamus group and a lot of neurons similar to the neurons of the cerebral cortex. The motor zone consists of many motor neurons (neural-like elements that generate control signals for the executive organs of a robot or an intelligent mobile system).

The artificial brain controls the operation of the robot's systems. The work of the nervous system of a robot, similarly to the nervous system of biological organisms, is based on unconditioned and conditioned reflexes. As already mentioned, the basis of any reflex is the reflex arc.

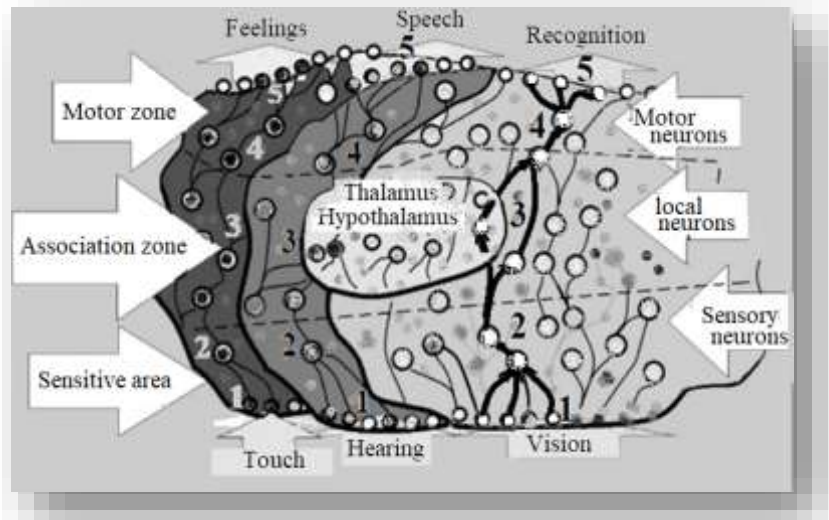


Figure 7 – Simplified diagram of the structure of the artificial brain on mmren-GN

The structural basis of the reflex arc is formed by neural circuits consisting of sensitive (2), intercalary (3), and motor (4) neurons. It is these neurons and their processes that form the path along which nerve impulses from receptors (1) are transmitted to the effectors of the executive organ (5) during the implementation of any reflex (Fig. 7).

Neurons of the thalamus-hypothalamus group collect information from the organs and sensitive areas of the robot and control the transfer of this information to the decision-making centers of the associative zone (analogous to the cerebral cortex).

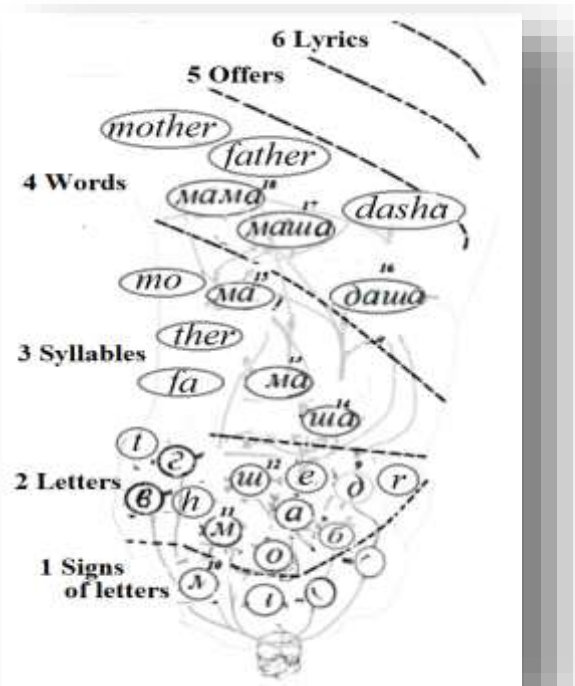


Figure 8 – Columns of an artificial brain cortex

In the structure of the associative zone (cortex of the artificial brain), in the process of perception, processing, and memorization of information, neural columns consisting of six layers are formed. Fig. 8 shows an example of a neural column containing symbolic information. In the first layer, as a result of the analysis of the perceived symbolic information, the characteristic features of letters are distinguished. In the second one, letters are formed as a result of synthesis.

In the third layer, as a result of the analysis, the characteristic features of words are distinguished: syllables, prepositions, endings, and parts that make up words. Words are synthesized in the fourth layer. In the fifth one, sentences are analyzed and characteristic combinations of words are distinguished. In the sixth one, words, sentences, phrases, and texts are synthesized. Moreover, all the information accumulated in the IM is remembered and stored in the mmren-GN, and it is compressed in each layer. One bit is one letter, one

bit is one word, one bit is one phrase, one bit is one sentence, and so on. This makes it possible to store huge amounts of information in mmren-GN.

Mmren-GN, which is an artificial brain, in accordance with the structure of the biological brain, consists of sensory, motor, and associative zones. Sensitive zones analyze information from receptors. The artificial thalamus collects information from all the senses of the robot and

sends it to the associative and motor areas. It turns out that each sensory system has its own “representative” there. The motor zones send commands to the working organs, and the associative zones connect the motor and sensory zones and store information related to learning, speech, thinking, and consciousness.

Consciousness can give an intelligent robot the ability to realize its existence, to feel, understand, and analyze what happens inside and around it. Modeling consciousness on neural networks is a difficult task, and at the moment scientists do not have full confidence in the possibility of solving it. In the world of science, there are heated discussions on the definition of consciousness and its implementation. There are studies and projects aimed at creating a model of the brain and artificial consciousness. One of them is the Blue Brain project. It aims to create a computer model of the brain that can help in studying how it works and understanding how the brain produces consciousness. For this, a powerful computer and mathematical models are used that allow you to simulate the work of neurons and the connections between them. Other projects are also researching the creation of artificial consciousness. However, for now, this remains more of a theoretical possibility as understanding the work of the brain and consciousness is still a difficult task for science.

In a child, consciousness begins to form from birth and continues to develop throughout childhood and adolescence. However, understanding when and how consciousness appears in a child remains the subject of scientific debates. There are various theories about how consciousness develops in a child. Some researchers believe that consciousness is formed based on biological and genetic factors, others suggest that the environment and experience play an important role in this process. In general, it can be said that the child's consciousness gradually develops starting from simpler forms of perception and reaction to the environment to more complex forms of thinking and self-awareness. According to studies conducted in France in 2013, the first signs of consciousness and memory in a child appear at the age of five months. The leader of the experiment, the cognitive neuroscientist Sid Kouider, believes that the brain activity of infants differs from that of adults, and although children can learn quickly at the beginning of their development, they are not yet aware of what they are studying [16]. Stanislas Dehaene, a professor of experimental cognitive psychology at the Collège de France, has published his research on the emergence of consciousness in children. According to it, the cerebral cortex, the epicenter of human consciousness, begins to form by six months of pregnancy. Based on research, neuroscientists suspect that even in the womb, the fetus becomes familiar with the sound of its mother's voice in the later stages of pregnancy. Dehaene believes that consciousness arises when different parts of the brain interact and communicate with each other at a high level. In contrast to the philosophical approach, using neuroimaging technologies, he tries to figure out how the human brain works when we are conscious [17].

According to other scientific studies, awareness of oneself as a separate person begins around the age of 18 to 24 months. At this age, children begin to understand that they are separate beings, different from other people and objects around them. They also become aware of their body and may begin to use the pronoun “I” to refer to themselves. However, the degree of awareness of oneself as an individual and the level of development of self-awareness can vary significantly depending on the individual characteristics of children and their experience of interacting with the environment.

The artificial brain based on mmren-GN can be considered as an organ of the “nervous system” of the robot, which controls the operation of its functional systems and ensures the performance of “higher mental functions” such as attention, memory, speech, and thinking. Regarding consciousness, without actually creating a robot with an artificial brain, it is difficult to say whether it will be aware of itself and its environment. Considering that the structure of the IM created on the basis of mmren-GN is similar to the structure of the biological brain, it can be assumed that the artificial consciousness of the robot appears in the process of its “life” in society.

7. Afterword

The article has described a conversation with ChatGPT which, according to the Alan Turing test, can be considered real artificial intelligence. It has been called a revolution in artificial intelligence. But since we know how ChatGPT is created and how it functions, we understand that this is far from being intelligence. So it was in 1997 with Deep Blue beating the world chess champion Garry Kasparov. This had the effect of a bomb explosion. Shock and delight. The victory of the computer was called the revolution in the field of artificial intelligence. But when the emotions subsided and people calmed down, they realized that there was no artificial intelligence there, it was the intelligence of the team that created the Deep Blue computer able to count at a speed of billions of operations second and choose the next move, just calculating its consequences to a winning result. So it was when the artificial intelligence system AlphaGo beat Korean Go champion Lee Sedol. In this case, the programmers managed to teach the computer not just to count moves but to constantly evaluate the position and look for the best continuations. Having received “initial knowledge about the rules of the game”, it learned itself. Almost 24 hours a day, it played with itself and improved. AlphaGo is based on deep neural networks, the advantages and disadvantages of which are described above. And it will always be so until an artificial brain similar to the human brain is created. Real AI or, according to modern terminology, artificial general intelligence will be created when a robot with an artificial brain is made, which will independently constantly learn in the process of “life”, form new knowledge and have a consciousness similar to a human one.

8. Conclusions

Artificial intelligence is one of the fastest-growing technologies of our time. It includes a set of algorithms and methods that enable computer systems to perform tasks that require intelligence. A special role in the development of artificial intelligence is played by neural networks that can learn from experience and improve their performance with each new task.

However, there are a number of challenges that need to be overcome when creating an artificial brain based on neural networks. One of these problems is the development of an efficient neural network architecture capable of simulating the complex work of the brain. The brain itself is a complex system, and we don't yet fully understand its functioning. However, researchers are proposing new neural network architectures that aim to more accurately model how the brain works. Another important problem is related to the training of neural networks. Training requires a large amount of data to enable networks to improve their efficiency. However, obtaining and structuring enough high-quality training data can be challenging. In contrast, an artificial brain built on neural-like growing networks can learn by actively functioning, just as living organisms learn by interacting with their environment. It can process and store large amounts of information, compressing it in each layer of the neural network structure, and be independent of storing information in cloud systems.

Given these and other possibilities, an artificial brain based on multidimensional multiply connected receptor-effector neuron-like growing networks is a unique structure. It is one of the most interesting and promising areas for the development of artificial intelligence.

However, it should be noted that the creation of an artificial brain based on neural-like growing networks is also associated with potential risks. Therefore, it is important to conduct further research and development to understand and manage these risks.

Despite this, creating an artificial brain based on neural-like growing networks may have incredible benefits for humanity. This technology can lead to the development of more advanced and intelligent robots, as well as improved functionality and accuracy of artificial neural networks.

In general, artificial intelligence and artificial brain based on neural networks represent important areas of research and development. We have unique opportunities to create technologies that can help us better understand the brain, develop more efficient and intelligent systems, and overcome complex challenges facing humanity.

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