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# An Object Recognition-Based Neuroscience Engineering: A Study for Future Implementations

**Mohammed Wasim Bhatt, Sparsh Sharma**

Department of Computer Science and Engineering, National Institute of Technology, Srinagar, J&K, India

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## ABSTRACT

The study of nervous system architecture and its behavior is an interdisciplinary science related to "Neuroscience." It contains each and every detail related to neuroevolution, molecular and cellular biostructure, anatomy, and pharmacology. To understand this complex structure and architecture of nervous system, a fast, reliable, and advanced technology is required. Object recognition (OR) plays a vital role to understand and adapt the complex system in an easy way. Object recognition provides a computational and cognitive platform to link neuroscience with the human–machine interface for proper interaction in the medical field. OR-computational neuroscience deals with the neural pattern through different models, whereas OR-cognitive science helps to understand the behavior mechanism of neural architecture. The goal of this research is to explain how the brain interprets and processes information using electrical and chemical signals. The paper contains OR-based models in the field of neuroscience. It examines neural representations, neuronal type communication, and neural learning in depth. This paper provides an overview of OR-based cognitive computational neuroscience as well as the models that go with it. A thorough examination of the applications is presented, followed by a discussion of potential future paths.

***Index Terms***—Cognitive neuroscience, neuroscience, OR computational, object recognition

**Corresponding author:**
Mohammed Wasim Bhatt,

**E-mail:**
wasim_2021phacse004@nitsri.net

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## I. INTRODUCTION

Neuroscience is a biology-based term that focuses on the operations of nerve cells inside the human brain that perform the complex cognitive process of running a human body system. To study the neuron activity, a highly accurate electrical tracking system is required [1]. The nervous system includes the brain, spinal cord, and a complex nerve network. This system communicates with the brain and the body. The brain controls all bodily functions. The spinal cord descends through into the back from the brain. It is composed of nerve strands that branch into every organ and part of the body. The brain receives and transmits messages to and from various parts of the body via this network of nerves. To advance cellular and molecular neuroscience, systems neurotransmitter system, cognitive and behavioral neuroscience, computational neuroscience, translational and clinical neuroscience, and translational and clinical neuroscience throughout order to better understand the molecular causes of both healthy brain function and neurological and psychological disease. The basic unit of the brain and the nerve system is termed as "Neuron." Each neuron is interconnected with the other through neuron receptors for signal transfer from one part to another. Many research works focus to model the neuron by using the mathematical approach with biological parameters as inputs [2]. Biological data have risen dramatically in recent years, owing to technical advancements that allow scientists to collect data from various levels and channels of a live system at the same time. Neuroscience, as well as genetics, developmental biology, and biomedicine, is evolving as a result of the advancement of OR-based medical sensors/equipments like electrophysiology workstations, cerebral blood flow device, electroencephalogram (EEG) systems, optogenetics equipment, and many more [3]. Neuroscience examines the activity of neurons and/or astrocytes as they exchange electrical signals using electrophysiology and other tools of a similar nature. In addition to sensitive anode and cathode that can record voltage movement patterns through a cell, sensitive imaging equipment is required for high-speed applications such as calcium imaging or greater implementations such as high-content image processing of fluorescently tagged neurons in brain tissue. Continue reading leads to learn more about electrophysiology and imaging equipment's applications in these fields.

The 21st-century neuroscience research is directed by the data [4]. Fig. 1 shows how the data play a crucial role in neuroscience. The input signal is received from the brain and analysis is done for effective operation. This architecture will aid brain research and diverse neuroscience investigations, allowing them to understand more about basic brain functioning. First, data are collected using different devices and sensors. Using data science, the data are filtered, aligned, and its characteristic properties are differentiated [5-7]. The data are then used to perform mathematical modeling of the nerve architecture, followed by analysis for various scenarios. The nerves generate huge amounts of data every second, and analyzing those data and extracting some meaningful information for medical science is really a challenging and complex task [8]. To extract meaningful knowledge from these data required data analytics, modeling, cloud computing, and many more such advanced technique. For all these techniques, data transfer from brain nerves to other devices and platforms is required [9].

With emerging object recognition (OR), various devices can be connected with each other for data transfer and analysis. These data could reflect a wide range of healthcare indicators collected by healthcare sensors using the OR [10].

To address complicated cognitive dysfunctions, scientists rely solely on data from current OR-based devices. They also gain more insights and research opportunities as the OR develops [11]. Patients are becoming more aware of the processes occurring in their neurological systems, and healthcare practitioners no longer have to rely on assumptions. There is a significant demand for technologies in this area [12-15]. It is no different in the realm of systems neuroscience. Many opinion pieces have been written in recent years about the importance of machine learning, artificial intelligence (AI), and other algorithms in neuroscience. Table I shows the different algorithms used in neuroscience. Various algorithms have been used for different types of designation in healthcare. At every stage, parameters are considered for effective monitoring and successful operation. With the help of all these platforms, the disease is diagnosed properly and the patient is treated. The above-mentioned section is the introduction to the manuscript. Section II is the related work which contains essential work done in the field. Object recognition-based architecture for neuroscience study has been discussed in section III. Results and respective discussion analysis have been done in section IV. Finally, section V concludes the paper with future scope.

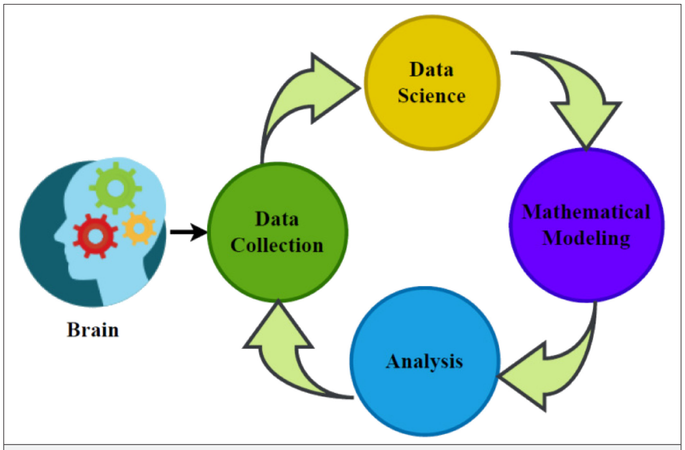


**Fig. 1.** Neuroscience cycle for analysis.

## II. RELATED RESEARCH WORK: FROM THEORY TO EXPERIMENT

A mathematical model is a simplified representation of reality. Despite its flaws and shortcuts, its pragmatic approach may aid us in better understanding the application and repercussions of brain-inspired systems in intelligent organizations. In the research work [16], Mahmud et al. propose an applicability-based architecture for cloud-based collective patient biomedical signal analysis. Connectivity models characterize the relationships between regions in addition to the localization of activated regions. In [17], a cloud-based healthcare system is proposed in which the neuroscience data are sent to the cloud for analysis and modeling. The main aim of the cloud was to do big data analysis and the researchers found that the overall performance was increased.

The brain collects knowledge in many areas of life, with parental and educational resources, as well as the social context in which we live, all playing a role. The ability to communicate facilitates this maturation, as well as the process of learning and personality development [18]. Our "mind" is developed from the moment we are born and probably much earlier in the embryonic stage, according to several philosophers and neuroscientists. Without language, there is no way to learn. When employed as a general notion, "language" may relate to the cognitive ability to learn and communicate, depending on philosophical opinions on the definition and meaning of language [19,20]. Natural language processing is currently one of the most popular subjects in machine learning. Scientists and large technology corporations have gambled on the deployment of four technologies to develop better integration between neurons and machines in order to build a cyborg civilization: the brain–machine interface (BMI), OR, extended reality (XR), and AI. Brain–machine interfaces allow patients with paralysis to interact with their surroundings by using brain activity to control external devices. Because it does not require active muscle use, BMI is a promising method for communicating with Amyotrophic lateral sclerosis (ALS) patients who are paralyzed. Object recognition refers to the process of identifying objects in images and videos. This is one of the most important applications of deep learning and machine learning. The term "extended reality" refers to all real-and-virtual combined environments and human–machine interactions enabled by wearables and computer technology (XR). The combination of these technologies will usher humanity into a new era of man–machine integration that is more natural, intuitive, interactive, and immersive. Researchers can use the Internet to influence the brain circuits of many animals simultaneously and independently, according to a new study. The researchers anticipate that this new technology can speed up brain research and diverse neuroscience investigations, allowing them to understand more about basic brain functioning and the causes of many neuropsychiatric and neurological disorders [21].

A research team from KAIST, Washington, and the University of Colorado, Boulder, model a wireless-based ecosystem consisting of OR infrastructure and wireless implantable sensors. This method shows that the brain neurons can be manipulated by external devices. This wireless system required a mini-computer-based platform which helps in communication via OR to the brain neurons. Neural learning, neuronal modeling, and neuronal communication are the three primary categories of computational neuroscience. An OR-based digital approach to collect data from the neurons is stated in the research article [22]. To reach the most appropriate conclusion, numerous studies are conducted in the field of neuroscience.

**TABLE I.** ALGORITHMS USED IN NEUROSCIENCE

| Algorithms/Techniques | Objectives | Parameters | Outcome | Description |
|---|---|---|---|---|
| Machine learning | 1. Large-scale neuroscience datasets can be analyzed automatically<br>2. Brain learning<br>3. To determine how the neurological system works | Neural electrical signals, chemical information | Pattern reorganization, brain mapping | It is best suitable for data analysis |
| Artificial intelligence | 1. Knowledge of the structure and activities of the brain<br>2. Adaptive learning | Neuron communication, feature extraction | Diagnostic procedure, optimize brain functioning | Deep neural networks, a type of artificial intelligence, aid experts in understanding how the brain functions and finding ways to improve it. |
| Fuzzy logics | 1. Facial pattern recognition<br>2. Image processing | Neuron activities, impulse, and spike signals of neurons | Disease diagnosis, heart-related diagnosis | Heart disease is diagnosed using the fuzzy resolution mechanism. |
| Big data | 1. Image classification<br>2. Electrophysiology interpretation | Head computed tomography images with accompanying radiologist reports and similar inputs | Can reduce clinical trial | It is critical that algorithms are rated on clinical outcomes rather than basic performance criteria based on retrospective data in prospective trials. |
| ANN | 1. Brain mapping<br>2. Neural mapping | Brain interaction pattern, neuron electric signals | Brain and neuron realistic design | It can be used specially for knowing the phases of the brain activities |

Neuroscience includes methods from cellular and molecular research to psychology and psychophysics of people. The goal of computational neuroscience is to explain how the brain interprets and processes information using electrical and chemical signals. Although this goal is not new, a lot has changed in the last 10 years. Because of advancements in neuroscience, we now know more about the brain, we have more computing power to simulate neural systems realistically, and we are learning new things from the study of simplified models of large networks of neurons [23, 24]. The system is divided into four layers as shown in the Fig. 2. Each layer plays an important role in collecting data from the neurons and sending it to the OR platform.

Furthermore, data from many emphasis subjects are measured, gathered, and communicated, even within the wireless sensor network (WSN). The compiled data are sent from the wireless sensor node to the receiver via an OR entry to create a database based on a person's

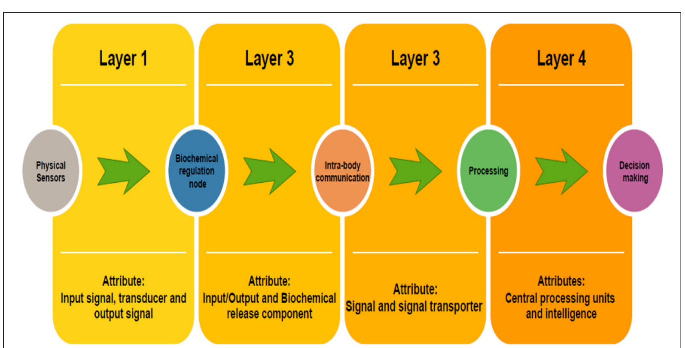


**Fig. 2.** Digital nervous system tools.

physiological and environmental indicators 24 hours a day, 7 days a week. By recognizing capacitive signal patterns, the neuron health status may be checked using the inbuilt vibration engine. The color-shifting lead can be utilized to convey more information about the current condition of health to the holder. Finally, a pushbutton is provided in case of an emergency. The first biometric shield is made out of the e-health detector platform V2.0, Raspberry Pi and Arduino. The next section will deal with neuron system architecture and OR-based approach for neurosciences. Few research articles are discussed in Table II to give a more intense overview of related works [22, 25-30].

## III. OBJECT RECOGNITION-BASED ARCHITECTURE FOR NEUROSCIENCE STUDY

The paper gives a summary of OR-based cognitive computational neuroscience and the associated models. It offers a comprehensive analysis of neural models, neuronal type communication, and neuronal learning. Our research demonstrates that no neural model is ideal or suitable for all applications and that the model should be chosen based on its intended function. As a result of brain-inspired learning made possible by OR sensors combined with voice-activated man–machine communication to access AI machine-generated knowledge, a new breed of intelligent businesses will emerge. This section of the paper deals with neuron building blocks and OR-based architecture to implement for better neuroscience study.

### A. Neuron Building Blocks

Neurons are the basic root of the central nervous system and brain. To handle a human being there is approximately more than 86 billion Neuron work simultaneously. There are three kinds of neurons: sensory neurons, interneuron, and motor neurons. Sensory neurons transmit signals from the peripheral (outer) geographic

**TABLE II.** RELATIVE RESEARCH STUDY HIGHLIGHTS

| References | Work Description | Outcome Description | Tool/Technique Used | Parameters Used |
|---|---|---|---|---|
| [22] | To develop an architecture that can approximate the pattern manifold to that of human brain | A nonlinear type line attractor has been proposed that may link patterns and even discriminate complex patterns. | Neural network associated with new learning algorithm | Human brain processes, high dimensional data |
| [25] | The aim was to recognize and study the behavior of two monkeys with human-related subjects | The outcome of this experiment shows that the monkey and human share a common neural sense that helps in object perception. | Image processing | 2D position, 3D rotation, and viewing distance of images |
| [26] | To access brain connectivity through nodes in vivo, the work introduces a scale-invariant edge weight and dimensionless system | The final results conclude that the use of the edge weight clearly demonstrates that to improve the reliability and network environment high seed density is required | Diffusion model based on rank 2 tensor | Edge weights, seed density. |
| [27] | The study examines the application of the FMR adaptation type paradigm to assess age-related deviation in the brain representation of objects over a range of sizes. | In both size and view adaptation experiments, both adolescents and adults were less accurate and slower to reply than youngsters. | FMR adaptation paradigm | Object size and visual angle for 3D images of objects |
| [28] | This study looks for evidence of epileptic seizure localization in the scale-invariant nature of brain activity. | The final results reveal that the spectral exponent related to ECoG data has identifiable properties that correspond to diverse brain areas and states. | Wavelet-based fractal analysis | Scale-invariant characteristics |
| [29] | This research proposed DCNN, HMAX and baseline shallow model to compare the invariant object detection with humans. | For lower variations in the images, the accuracy of the model approximates the human subject; however, for high variations in images, the model outperforms human subject. | DCNN model, HMAX model, Baseline shallow model | Images with different variations in size |
| [30] | The goal of this research is to look into the feature-based mechanism that is involved in human recognition as object. | The final results show that the human outperforms the model when variations are more complex | Bubble method | Position of image, size variation, in-plane rotation, and in-depth rotation |

FMR, Functional magnetic resonance; EcoG, Eastern Cooperative Oncology Group; DcNN, deep convolutional neural network; HMAX, Hierarchical Max-pooling.

areas of your body to the central nervous system. Motor neurons transmit signals from your central nervous system to your muscles, skin, and glands (motoneurons). Interneuron connects multiple neurons in the brain and spinal cord. Motor neurons, which control muscle contractions, have a cell body, a long axon, and also dendrites on either end. Astrocytes and glial cells offer structural support, enable ion exchanges, and give sustenance to the neurons, among other things. A single neuron consists of five important parts which are stated as follows and the basic stucture of single neuron is shown in Fig. 3

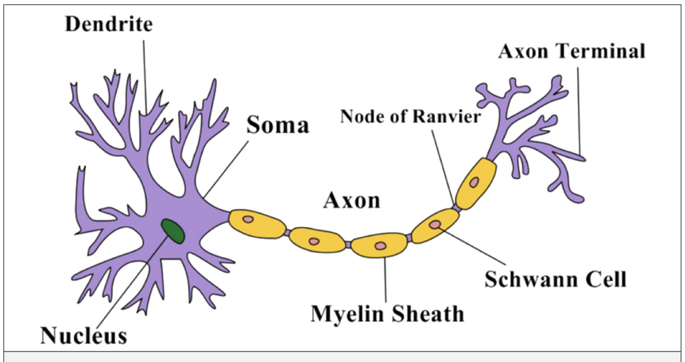


**Fig. 3.** Basic structure of neurons [22].

1) Dendrites: It helps in receiving and processing the signals. This signal is then forwarded to the cyton. It can receive signals in terms of excitatory or inhibitory.
2) Soma: The neuron's cell body. It houses the nucleus and is responsible for a neuron's basic functions.
3) Axon: It emerges through the cell body via Axon Hillock, a site in the shape of a cone. The axon then splits into multiple sub-branches in the shape of fine filaments named telodendria and forms bulbous-type swellings known as axon terminals at the cell's end (or bouton). The axon transports impulses away from the cyton. On target cells, these axon terminals form connections.
4) Myelin sheath: Its aim is to act as a barrier between the neuron and the outside world. It inhibits electricity from escaping through the nerve.
5) Node of Ranvier: These are the myelin sheath's periodic gaps. Saltatory conduction aids in the quick transmission of nerve impulses.
6) Schwann cell: Schwann cells are a type of glial cell that keeps myelinated and unmyelinated peripheral nerve fibers alive.
7) Axon terminal: Axon terminals are tiny swellings present at the axon's terminal ends. They are usually where you will find synapses with other neurons.

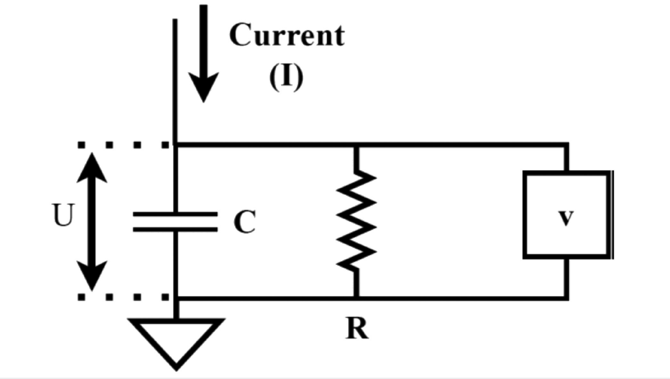


**Fig. 4.** Simple neuron model.

Using the earlier details, the neuron can be modeled in different ways for different parameter studies. Modeling each neuron seeks to replicate the way neurons behave when they are stimulated and exposed in response to an external stimulus, which can be applied externally by the researcher or internally by connections from other networked neurons. One of the most basic ways for studying a neuron's firing events is the Integrate type Fire model. In 1907, Lapicque proposed it [31]. When the neuron membrane potential passes a particular threshold value, *v*th, an action potential is generated. An action potential is produced when a neuron responds to the threshold or suprathreshold stimuli. This process has three phases: depolarization, overshoot, and repolarization. An action potential makes its way along the axon's cell membrane until it reaches the terminal button. A neurotransmitter is released into the cytoplasm cleft as soon as the terminal button depolarizes. When a neurotransmitter unites with its neurotransmitters on the cell's postsynaptic membrane, the target cell is stimulated or inhibited. Fig. 4 shows how a neuron is portrayed as an resistor–capacitor (RC) circuit. Using this simple neuron model, a simple overall OR-based platform can be designed.

### B. Sensors Used in Neuroscience

Sensors play a key role in neuroscience applications. The main aim of the sensor is to collect real-time data from the neurons and send it to the receiver. This makes it easier to create solutions for measuring complex health outcomes in non-specialist and remote locations. The functioning of the brain is extremely complicated. As a result, there are a plethora of tools available to assess various aspects and characteristics of brain activity. The vast majority of the solutions we look into are creating technologies that have shown their utility in clinical trials, at least in terms of giving exploratory endpoints and data to supplement other study endpoints evaluating the same ideas of interest. The primary technologies considered are summarized in Table III [32].

### C. Object Recognition for Neuroscience Engineering

Object recognition plays a vital role in neuroscience. Fig. 5 shows object recognition-based neuroscience engineering architecture. It has seven basic steps as follows:

1) Sensor data extraction: Data extraction is defined as the act or process of extracting data from data sources for further processing or storage. Data transformation and maybe metadata addition are usually done after import into the intermediate extraction system before output to the next stage of the data pipeline.
2) Noise reduction: Any data coming from outside sources consist of noise. To eliminate this noise and pass better data for processing, noise reduction technique is used.
3) Channel: Visual recognition is hampered by dynamic disturbances, which can obfuscate the item's identity, delay recognition, and possibly result in incorrect identification of the object or its attributes. The channel helps to separate the coding and encoding parts.
4) Decoder: The decoder's goal is to determine the object's identity and classify its properties. In effect, the decoded message will reflect the object that the Identity tracker (IT) has identified based on the representation that the lower visual stages have sent on to the IT.
5) Interleaver: An interleaving operation is used to mimic picture processing. The biological rationale for the interleaver stems from the need to parse the information output by the decoder into a set of qualities, as well as the importance of the attributes for recognition.
6) Memory: It helps to combine the datasets and the input of interleaver.
7) Result: The final output of OR based is based on the logic, sensor, and training done with the optimization tools.

Object recognition devices or nodes generate data in cloud-based OR systems as a result of numerous neuroscience applications. These nodes collaborate with one another through predetermined social features, notably the "Trust Compositions," much like human relationships. On the OR and user ends, the values of these social

**TABLE III.** SENSORS USED IN NEUROSCIENCE [32]

| Sensors | Place of Measurement | Data Complexity | Deploying Complexity | Focus Area |
|---|---|---|---|---|
| PET | Brain | Complex | Complex | Brain nuclear image |
| EEG | Brain | Complex | Easy | Electrical activity of brain |
| PPG | Heart | Medium | Easy | HRV response |
| GSR | Skin | Medium | Easy | Skin conductance |
| MEG | Brain | Complex | Complex | Brain magnetic activity |
| EKG | Heart | Complex | Complex | HR and HRV |
| F-EMG | Facial muscles | Complex | Easy | Facial Recation |

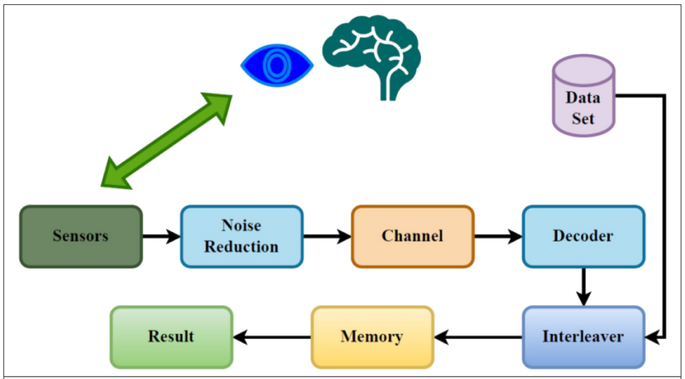


**Fig. 5.** Object recognition-based neuroscience engineering architecture.

attributes are propagated. Object-recognition based neuroscience employed several advanced sensors to monitor the status of neuron activity. In simple terms, the OR-based neuroscience has three basic stages. The first stage is sensor data acquisition for OR, in which sensor data is transferred to the cloud. Stage 2 defines the storage and data interface. In the last stage, the real-time data is interfaced according to the requirement. This last stage helps as feedback for OR systems. Fig. 6 shows the object recognition based Stages for Neuroscience.

## IV. RESULTS AND DISCUSSION

As per the data from the last 2–3 years, the use of OR has been increased in neuroscience. In upcoming years, the number of OR-based neuroscience interface is going to increase many folds. In the execution of the solution and the outcomes, users, doctors, health criteria, and requirements were taken into account. Fig. 7 shows Object recognition-based neuroscience (%) [33-35].

Test–retest reliability using the same and different units of the same device should be used to verify intra- and inter-device reliability of OR-based neuroscience. The intraclass correlation coefficient is commonly used to determine this. In order to ensure device equivalence between batches and with the reliability data provided, device producers must be able to verify that devices are produced in compliance with a quality system. When used in a clinical trial, outcome measures and derived endpoints should be sensitive enough to detect changes when they occur. To demonstrate this, controlled trials with an intervention that is known to generate a change in the outcome of interest are typically utilized. According to environmental psychologists, investigations that isolate stimuli provided to participants in user studies are not predictive of actual activations in human physiological characteristics that would occur in naturalistic situations. Because this study was directed at

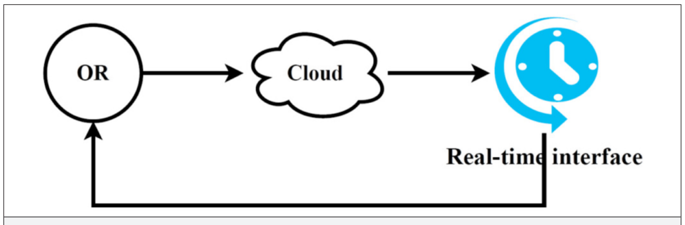


**Fig. 6.** Object recognition-based stages for neuroscience.

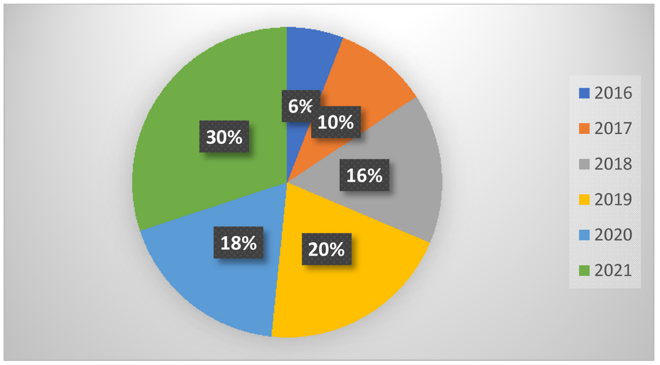


**Fig. 7.** Object recognition-based neuroscience (%) [33-35].

the human experience in spaces, it was decided to keep the spaces where architectural design elements were altered as realistic as possible and only configure the design features that were being evaluated. This was a source of concern for environmental psychologists, which is why realistic spaces were built.

Cognition is defined as the ability to see and react, process and understand, store and retrieve information, make decisions, and produce appropriate responses. Brain cognitive functions enable us to receive, select, store, transform, develop, and recover information from external stimuli. Through this process, we can better understand and relate to the world. Cognitive dysfunction, such as issues with attention, concentration, and memory, has been related to a variety of mental illnesses. Cognitive function testing can assist, detect, and analyze the impact of treatment by identifying which brain systems are involved in the symptoms. In clinical trials, cognitive function is generally assessed in a laboratory setting utilizing a battery of computerized tests, such as the Clinical Data Repository (CDR).

## V. CONCLUSION

A thorough examination of neural models, neuronal type communication, and neuronal learning is offered. Our findings show that no neural model is perfect or appropriate for all applications and that model selection must be based on the intended function. A new breed of intelligent enterprises will emerge as a result of brain-inspired learning enabled by OR sensors combined with voice-triggered man–machine communication to access AI machine-generated knowledge. Expertise in neuroscience, AI-based machine learning, and the deployment of OR infrastructures are required to build this type of business. The challenge of creating a "brain-inspired" intelligent organization with "mind" supporting technology, first and foremost, necessitates architectural and organizational know-how, as well as a broad humanitarian foundation. If the future road toward "brain-inspired" intelligence and corporate "mind" development is ignored, current efforts to digitally alter firms may be short-lived. The advantages of OR over static, traditional systems are shown by execution speed and risk reduction in decision-making that is aligned with the corporate mind's ideals. The human contribution to intelligent organizations is centered on using creativity, common sense, and the capacity to see beyond existing boundaries to solve complicated challenges. The OR's key success factor will be the quality of managing these human resources.

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Mohammed Wasim Bhatt completed his B.Tech in Electronics and Communication Engineering from Baba Ghulam Shah Badshah University, J&K, in 2017 and M.Tech in Computer Science and Technology from Central University of Punjab, Bathinda, in 2020 and Ph.D (pursing) from National Institute of Technology, Srinagar. His area of interest includes machine learning, neuroscience, artificial intelligence, and Internet of things.

Dr. Sparsh Sharma has been declared qualified for the award of the degree of Doctor of Philosophy (Ph.D.) in Computer Science and Engineering by Shri Mata Vaishno Devi University (SMVDU), Katra. He worked on the topic "Enhancing Security and Utilization of Resources in VANETs and VANET Cloud Environment" under the supervision of Dr. Ajay Kaul, Associate Professor, School of Computer Science and Engineering, SMVDU, Katra. Mr. Sparsh has published various research articles in reputed SCI/SCI-E and SCOPUS-indexed journals. Presently, he is working as Assistant Professor in the Department of Computer Science and Engineering, National Institute of Technology, Srinagar, J&K, India.