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# Incremental Learning with Self-Organizing Bayesian Adaptive Incremental Network (SOBAIN)

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**Abstract:** Neural networks and artificial intelligence have revolutionized how machines learn by mimicking aspects of human cognition. One key area in this field is the ability of agents to understand and imitate actions involving various objects, allowing them to pick up new skills by observing others. Understanding and imitating how others interact with different objects has become a big topic since it allows learning new skills by simply watching others. By constantly updating their own knowledge, lifelong learners can build on what they know over time. But the environments that artificial agents deal with are very different. Existing models designed for "lifelong learning" typically work with simplified experiments and datasets made up of static images, which limits their effectiveness for real-world applications. In this study, we propose a developmental model focused on how agents can learn about objects and actions through sensorimotor feedback, enabling humanoid robots to mimic actions more naturally. Our approach, "SOBAIN," works in three stages: neuron activation, neuron matching, and neuron learning. First, neurons activate based on specific traits that determine if they should "fire" or not. Then, we match the best neuron by comparing activation levels. At each learning point, new neurons connect to the network to match learned data. The final stage uses this network to refine and apply learned information, helping address memory loss issues in lifelong learning. By using these techniques, SOBAIN helps robots adapt their upper body movements in line with the sensor's feedback, creating a chain of neurons that builds over time as the robot learns new actions.

**Keywords:** Adaptive; Bayesian; Incremental; Network; Self-Organizing; SOBAIN

## 1. Introduction

Imitation learning is a method of acquiring novel skills by observing and learning from the actions of other agents. Within the realm of robotics, the significance of imitation learning is notable. Numerous studies indicate that the ability to imitate develops at an early stage in life [1]. Nonetheless, machine learning models typically function in scenarios where the entire dataset is presented during the training phase, assuming that the identified patterns in the data will remain static. On the contrary, Incremental learning adjusts to sequential data or addresses the challenge of concept drift, which emerges as data evolves over time. Therefore, continual learning [2] is well-suited for scenarios where data incrementally accumulates over time. Incremental learning or lifelong learning proves valuable in situations where data cannot be provided all at once, increasing gradually through feedback, and direct access to previously acquired knowledge is restricted.

Continuous learning [3] or incremental learning involves acquiring new information while retaining previously gained knowledge, ensuring a seamless integration of fresh insights without erasing existing learning or knowledge. Both humans and animals possess the capacity for lifelong learning, allowing them to continuously acquire, refine, and transfer knowledge and skills throughout their lives. This ability is facilitated by a complex set of neurocognitive mechanisms that contribute to the development and specialization of sensorimotor skills, as well as to long-term memory consolidation and retrieval [4]. In the real world, computational systems encounter constant streams of information, necessitating their ability to learn and retain multiple tasks amidst dynamic data distributions [5]**.** For example, an autonomous agent engaging with its environment must glean insights from its experiences, demonstrating the capacity to gradually acquire, refine, and transfer knowledge over extended periods.

The primary challenge in computational models concerning lifelong learning is their susceptibility to either catastrophic forgetting or catastrophic interference [6]. In other words, the process of training a model with new information can disrupt previously acquired knowledge. This occurrence often results in a sudden decline in performance or, in the worst-case scenario, the complete replacement of old knowledge with new information. Methods in Computational Intelligence also serve as potent instruments for deciphering structural details from digital datasets. Traditional Deep Neural Networks and convolutional Neural Networks (DNNs, CNNs) encounter difficulties in consistently learning from a data stream while preserving acquired knowledge. Overall, achieving a continuously trainable AI system faces several key hurdles, including the issue of catastrophic forgetting during the assimilation of new data, the absence of model scalability concerning the inability to expand the model's size with a continuously increasing volume of training data, and the incapacity to transfer knowledge between different tasks. Several recent methodologies [7] aim to alleviate the issue of forgetting in neural networks by directly simulating continual learning within the network responsible for task-solving. Especially, [8] proposed initially training a distinct model exclusively for the new classes, followed by the integration of the two individual models, each trained on data from separate sets of classes (old and new). This integration is achieved through an innovative double distillation training objective. The consolidation of the two existing models is facilitated by leveraging publicly available unlabeled auxiliary data, addressing potential challenges arising from the unavailability of original training data. The suggested model attains accuracy rates of 58.06 and 55.89 for CIFAR-100 and CUB-200, respectively.

In [7] authors introduced a hierarchical CNN network designed to prevent catastrophic forgetting and capitalize on previously acquired features when confronted with new tasks. The network dynamically expands as new classes are introduced, incorporating these classes as additional leaves within its hierarchical structure. The branching is determined by the similarity of features between the new and existing classes. The Tree-CNN's initial nodes categorize inputs into broader super-classes, and as we progress towards the network's leaves, more refined classification takes place. This innovative model facilitates the utilization of convolution layers previously learned, enabling their application in the expanded network for enhanced adaptability. Testing was conducted on models designed for CIFAR100 datasets. The accuracy scores for Tree-CNN-5, Tree-CNN-10, and CNN-20 were 69.85, 69.53, and 68.49, respectively.

Despite the advancements in lifelong learning methodologies within the field of artificial intelligence, there remains a notable research gap in addressing the scalability and adaptability of models to evolving data distributions, as well as the mitigation of catastrophic forgetting. Existing approaches often struggle to efficiently integrate new information while preserving previously acquired knowledge, hindering the seamless accumulation of skills over time.

1. What does the system store in episodic memory for all actions taken and how can we update data that has previously been stored there?
2. How the robot can employ a self-organizing strategy to incrementally develop new knowledge without distorting previously learnt material, and maintain for quick and accurate retrieval?

3. How the system can get to maximum results and how maximum accuracy can be achieved using episodic memory and SOBAIN model?

This paper introduces a self-organizing Bayesian adaptive incremental network named SOBAIN for incremental learning, it is an efficient and successful approach consisting of three stages videlicet Neuron Activation, Neuron Matching, and Neuron Learning. When necessary, a number of "adaptive recurrent growing when required" construct SOBAIN (ar-GWR) [9]. The network comprises an adaptive threshold responsible for establishing the sensory information threshold. SOBAIN can create and arrange neurons through its three stages. The suggested approach continuously assimilates new information in neuron matching while retaining awareness of previous information in neuron learning. Our contributions aim to address the challenges of catastrophic forgetting and model scalability by providing a comprehensive framework for continual learning in artificial intelligence systems.

The remaining of this paper is organized as follows. Section II presents the related work of the proposed method. The proposed Methodology is shown in Section III while results are discussed in Section IV. Conclusions are finally presented in Section V.

## 2. Related Work

The aspiration for continuous learning has been a persistent objective in machine learning. This learning paradigm is alternatively known as incremental learning and more specifically as lifelong learning [10], mirroring the way humans and other animals continually acquire and refine their knowledge [11].

Memory-based systems, dating back to early approaches, have historically been employed to avert catastrophic forgetting by storing and rehearsing old data continuously.

However, in the era of big data, the explicit storage of old data or data streams becomes impractical [12], necessitating alternative strategies. In conceptual terms, these strategies can be classified into three categories including regularization methods, complementary learning systems, and dynamic architectures [4].

Various strategies combat catastrophic forgetting in neural networks. Elastic Weight Consolidation (EWC) is a regularization technique that maintains a balance between old and new task performance by penalizing weight updates [13]. Complementary learning systems, realized through dual-memory systems, model distinct brain functions for episodic memory retention and generalization [14]. Dynamic architectures, such as Progressive Networks, adapt to new tasks by sequentially incorporating subnetworks, demonstrating robust performance in reinforcement learning. However, an associated drawback is the escalating network complexity with an increasing number of tasks [15].

To retain previous information and deal with catastrophic forgetting data transmission to earlier steps has been made more effective with the Gradient Episodic Memory (GEM) model [16]. The key component of GEM is episodic memory, which is utilized to remember a group of examples observed during a certain job in order to prevent catastrophic forgetting. Compared to other regularization techniques like EWC (Elastic Weight Consolidation) at training, this strategy uses a lot more memory.

[17] Involves the review and categorization of relevant works, examining various perspectives in addressing the issue of catastrophic forgetting in classification tasks. The adopted solution strategies encompass architectural approaches, regularization methods, and rehearsal and pseudo-rehearsal strategies.

The study [18] compared Echo State Networks (ESN) and Long Short-Term Memory (LSTM) networks for continuous gesture recognition, particularly focusing on real-time applications in robotics and rehabilitation. Despite the identified challenges like sub-gestures and gesture variability, the ESN framework exhibited comparable performance to the LSTM network but with significantly lower training times. This suggests that ESNs are viable models for real-time continuous gesture recognition, offering a balance of efficiency and accuracy in applications requiring swift responses, such as those in robotic or rehabilitation tasks. The study also proposes potential enhancements for both experimental methodology and network architecture based on the comparative analysis.

Conventional Deep Neural Networks (DNNs) and Convolutional Neural Networks (CNNs) face challenges in maintaining acquired knowledge while continuously learning from a data stream.

In [10] authors introduced a hierarchical CNN network designed to prevent catastrophic forgetting and capitalize on previously acquired features when confronted with new tasks. The network dynamically expands as new classes are introduced, incorporating these classes as additional leaves within its hierarchical structure. The branching is determined by the similarity of features between the new and existing classes. The Tree-CNN's initial nodes categorize inputs into broader super-classes, and as we progress towards the network's leaves, more refined classification takes place. This innovative model facilitates the utilization of convolution layers previously learned, enabling their application in the expanded network for enhanced adaptability. Testing was conducted on models designed for CIFAR100 datasets. The accuracy scores for Tree-CNN-5, Tree-CNN-10, and CNN-20 were 69.85, 69.53, and 68.49, respectively.

The approach presented [19] aims to combat the problem by incrementally training deep neural networks using new data and a limited exemplar set representing samples from the old classes. This involves a loss function that incorporates a distillation measure for retaining knowledge from old classes and a cross-entropy loss for learning new classes. Notably, the incremental training is conducted in an end-to-end manner, jointly optimizing data representation and the classifier, providing assurances that recent methods may lack. The proposed model achieves mean accuracy scores of 63.8 for CIFAR-100 and 69.4 for ImageNet (ILSVRC 2012).

In [8] proposed initially training a distinct model exclusively for the new classes, followed by the integration of the two individual models, each trained on data from separate sets of classes (old and new). This integration is achieved through an innovative double distillation training objective. The consolidation of the two existing models is facilitated by leveraging publicly available unlabeled auxiliary data, addressing potential challenges arising from the unavailability of original training data. The suggested model attains accuracy rates of 58.06 and 55.89 for CIFAR-100 and CUB-200, respectively.

Conventional Deep Neural Networks function with fixed-size training data or predefined batches, leading to challenges of continuous forgetting. The introduction of new data results in the loss of previously learned patterns, emphasizing the need for an incremental learning system with minimal cues to consistently adapt actions or responses over time. In contrast, Growing When Required (GWR) and gamma GWR have demonstrated greater success in achieving favorable results compared to traditional approaches. The suggested approach is self-organizing and adaptive to input. To achieve classification through unsupervised learning, labels are assigned to neurons based on their activation frequency for specific labels. GWR [20] yielded outcomes on the CAD-120 dataset, with accuracy, precision, and recall serving as evaluation metrics. It achieved 79% accuracy, 80.5% precision, and 78.5% recall.

In another study gamma GWR [21]. A widely recognized approach to address the issue of neuron forgetting in computational models involves implementing a maximum age for connections. This strategy entails removing connections associated with neurons whose activation values do not meet a specified threshold or have not fired frequently over time. By setting a maximum age criterion, the computational model optimizes its equilibrium between stability and adaptability, preventing the undue forgetting of information and ensuring that neurons actively contribute to the learning process.

## 3. Methodology

Our proposed method SOBAIN incremental learning with Self-Organizing Bayesian Adaptive Neural Network is generated by various numbers of (ar-GWR). The SOBAIN model has an episodic memory that is working for lifelong learning. In lifelong learning networks process new incoming data as well as update already existing data. The ar-GWR rapidly learns the series of past experiments in episodic memory the ar-GWR learns and replicates input information in the episodic memory layer by adding neurons to the layer.

A. Dataset: We used the KTH dataset [22] for our experiments, which includes videos of six actions: walking, jogging, running, boxing, hand waving, and hand clapping. We wrote a Python script to convert these videos into images with a resolution of 160 × 120 pixels. The dataset features 25 people performing these actions in different environments with static cameras. To add variety, the settings included outdoor scenes, outdoor scenes with scale variations, people wearing different clothes in the same outdoor location, and indoor scenes. 75% of the images from each action, we used as training and 20% we used as test data. Then, finally we used 5% for validation purposes.

B. Episodic Memory: An episode is created by a series of events and is stored in the episodic memory together with other episodes. We introduce temporal links that reveal the network's recurrent neurons' activity patterns. The sequence of neurons that have been stimulated during the learning process is encoded by the temporal connections (prior winner node and present winner node).

For each learning iteration, two neurons are progressively stimulated, increasing the temporal link between them by one. Every learning process establishes a temporal connection between neurons when we get fresh information at time t that is linked to previously active neuron j-1 at time t-1 [23].

$$Q^{new}_{(b,j-1)} = Q^{old}_{(b,j-1)} + 1$$
$$g = argmax\ Q_{(m,n)}$$

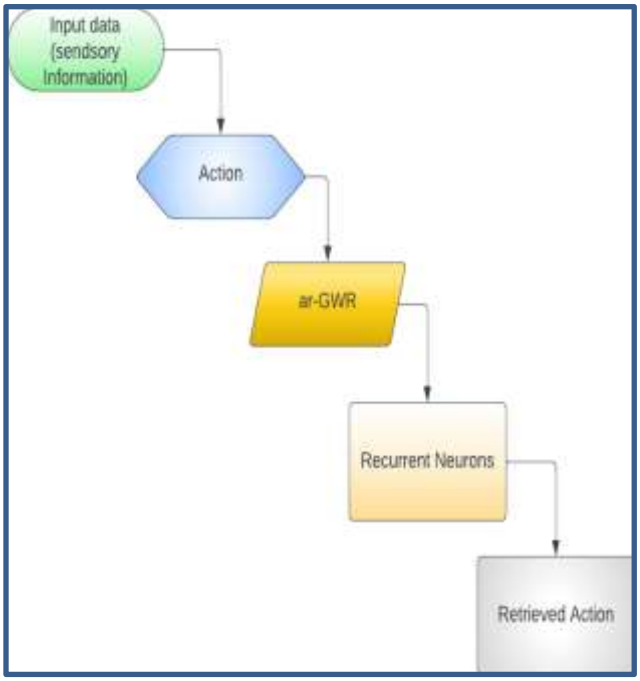


**Figure 1.** Architecture of SOBAIN

Where $g$the next neuron is can be obtained from the encoded temporal series by selecting the largest value of Q for each recurrent neuron m, and n is the neighbor of m. Without requiring any input data, the activation sequence of recurrent neurons may be restored. The edges and neighbors of a node should be deleted if they are no longer present. The procedure of deletion is finished.

C. Experimental Setup: To execute the proposed method as in Figure.1, we have to create two memories working memory and episodic memory, which are connected to each other. Firstly working memory is created which takes images and extracted features as input using SOBAIN, and then finally output becomes the input of the episodic memory. The episodic memory of the SOBAIN model is useful for lifelong learning. Networks that process lifelong learning update and process new data that comes in. The adaptive recurrent, (ar-GWR) network that incrementally generates neurons and topological connections in the layer is present in episodic memory, where it is used to determine the spatiotemporal relationship of incoming input. The ar-GWR selects the winning neuron based on a real input and temporal relationship by assessing the activity value of neurons. The series of previously excited neurons that are connected with a time delay is known as a temporal connection. The episodic memory layer of the ar-GWR quickly learns the sequences of previous observations, which it then reproduces using instances of input data.

As SOBAIN, a comprehensive model, integrates two key memory systems, namely working memory and episodic memory as shown in Figure.2, tailored for continuous learning. In the dynamic working memory layer, the ar-GWR adeptly learns and encodes succinct representations of incoming data samples by seamlessly integrating neurons into the layer. Concurrently, within the episodic memory layer, the ar-GWR swiftly assimilates the sequence of past experiences (events), skillfully encoding the temporal connections among these experiences derived from the working memory layer. This sophisticated architecture facilitates the model's ability to adapt and extract meaningful patterns for enhanced learning and memory consolidation.

When new input is received, the system checks existing neurons to find the best matching neuron (BMN). This replay process stabilizes the network. If no BMN is found, the network creates new neurons, enhancing its plasticity.

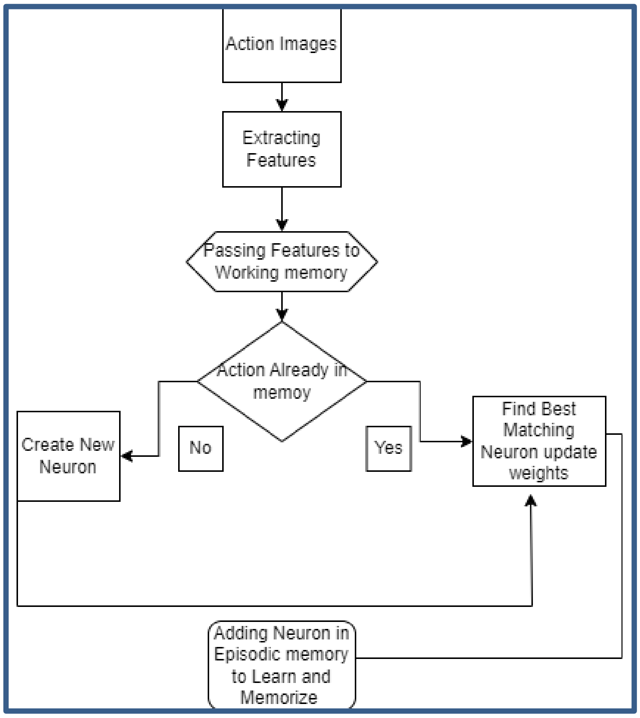


**Figure 2.** Flow Chart of the proposed model for incremental learning using SOBAIN approach.

The ar-GWR has three principal stages:

1) Activation of Neuron
2) Matching of Neuron
3) Learning of Neuron

We will use the Neuron Activation to find the best-matching neuron. The performance of a neural network is determined by the activation functions, which are mathematical equations. The activation function is connected to each neuron in the network, which controls whether or not that neuron should be triggered (also known as "fired"). The performance of each neuron frequently depends on activation functions. Each data set's activation functions, which are measured using thousands or even millions of neurons, must be computationally efficient. The input layer is where the neuron receives its input. The following layer receives the weight assigned to each neuron.

The next layer will be ar-GWR. An activation function allows backpropagation and to learn complex data set with high levels of accuracy. The ar-GWR have the activation function to determine the best neuron matching (BMN) w_b based on the input x (t).

$$b = arg\ min(T_j) \quad (1)$$

Where

$$T_j = \alpha \parallel x(t) - w_j \parallel^2 + \sum_{k=1}^{k} . \alpha^k \parallel E_k(t) - e_{k,j}(t) \parallel^2 \quad (2)$$

$$E_k = \beta . w_{j-1} + (1 - \beta) . e_{k-1,j-1} \quad (3)$$

**Table 1.** Parameters *for ar-GWR algorithm*

| Parameter | Meaning |
|---|---|
| $w_j$ | Weight of winning node |
| $\alpha , \beta$ | Contributing factors that control the effect of current input |
| x(t) | Input |
| $w_{j-1}$ | Weight of previous winning node |
| $E_k$ | Global element |
| ${}^{k}_{j}e$ | Temporal element attributes |

When we have input x(t) then the activation value of BMN is calculated as $a_b(t) = exp(T_b)$ where $T_b$ calculated by using the equations (1) to (3). We will further use these equation to achieve our goal. Episodic memory incorporates incremental learning, functioning much like human memory, which recalls past events as episodes. These episodes are interconnected, forming a network of related memories. To mimic the human hippocampus, we introduce temporal connections in the network, enabling it to learn and remember activation patterns of recurrent neurons. The purpose of these connections is to encode sequences of activated neurons during the learning phase. In each iteration, if two neurons activate consecutively, a temporal connection is formed by increasing the value of a counter C linked to that connection. For instance, if neuron k activates at time t and neuron k−1 activates at t−1, the connection between them is incremented by 1.

This mechanism identifies the sequence of activated neurons. For any given neuron, its next neighbor is determined by the highest value in the encoded temporal sequences. This approach allows episodic memory to reconstruct the activation order of neurons, enabling the network to remember and recall the sequence of activations associated with specific human actions in images.

When new input is received, the system checks existing neurons to find the best matching neuron (BMN). This replay process stabilizes the network. If no BMN is found, the network creates new neurons, enhancing its plasticity.

## 4. Results and Discussion

The modern world generates new data every second, leading to dynamically changing information known as sequential data. To handle this type of data, incremental learning is essential. Incremental learning processes data sequentially, in chunks, or by breaking down complex data into smaller sequences. This approach allows systems to adapt to new information while retaining previously learned knowledge. Incremental learning builds on prior experiences, enabling the development of autonomous and interactive models. In our proposed model, we focus on implementing incremental learning while addressing the stability-plasticity dilemma to avoid the issue of catastrophic forgetting.

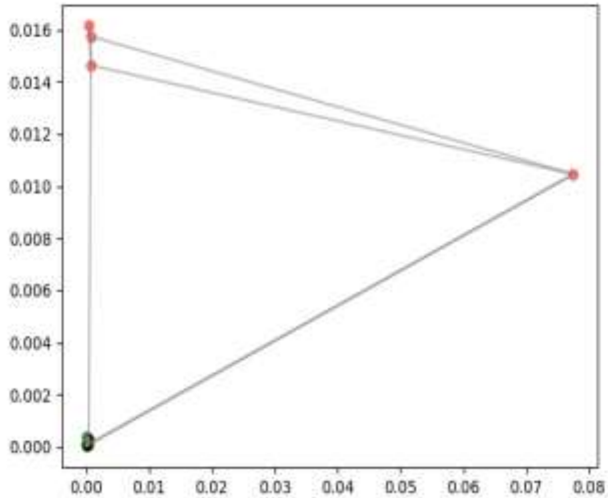


**Figure 3.** Neurons Activation over Time

The proposed model processes images by first extracting key features using SOBAIN in the Working Memory. These features, which represent all relevant aspects of the input image, are passed to the Episodic Memory. Here, the input images are grouped into clusters based on their similarities. The Working Memory's output is used by the Episodic Memory to train on the input and learn the sequence of neuron activations for specific patterns in the data, forming connections. It clusters related data and creates new clusters for unfamiliar data without requiring the number of clusters to be predefined. Additionally, any node in the network with zero edges—indicating it represents no information—is deleted. This mechanism mimics human hippocampus memory by helping the model retain meaningful information. After training, test samples are sent to both Working Memory and Episodic Memory. Episodic Memory then recalls stored information from previous experiences to identify whether the object or action has been learned before.

SOBAIN, our proposed model achieved 89 percent accuracy in identifying correct actions from input images that we used for validation. We compared our results with [20], [21], [23] and Gamma-GWR by comparing accuracy and number of neurons creation. GWR makes 7501 neurons for 35000 samples with 84.6% accuracy, similarly Gamma-GWR created 7950 neurons of 35000 sample of data with 88% accuracy. However, SOBAIN made 7001 neurons for 50659 samples with more stability and plasticity balance and achieve accuracy of 89% keeping the stakes high.

**Table 2.** Comparing the accuracy of the proposed model with other incremental learning approaches.

| Architecture | Dataset | Samples | No. of Neurons | Accuracy |
|---|---|---|---|---|
| GWR [20], [21], [23] | CAD-120 | 18000 | 3700 | 80.5% |
| Gamma-GWR [20], [21], [23] | COEe50 | 164866 | 7950 | 79.43% |
| SOBAIN | KTH | 50659 | 7001 | 89% |

## 5. Conclusion and Future Work

In this study, we proposed an algorithm capable of learning the spatio-temporal relationships in image patterns and clustering input images of human actions into their respective groups. The algorithm also develops an episodic memory that learns, stores experiences as episodes, and recalls what it has learned. In the future, we plan to test the algorithm on various datasets and integrate it into a robot that can utilize recall memory to mimic human behaviors based on images. We aim to optimize the algorithm for continuous learning of actions and gestures, enabling the robot to recognize and replicate action patterns in real-time by segmenting time-series data according to human behavior patterns.

## References


1. J. Hua, L. Zeng, G. Li, and Z. Ju, “Learning for a robot: Deep reinforcement learning, imitation learning, transfer learning,” Feb. 02, 2021, MDPI AG. doi: 10.3390/s21041278.
2. O. Ostapenko, M. Puscas, T. Klein, P. Jähnichen, and M. Nabi, “Learning to Remember: A Synaptic Plasticity Driven Framework for Continual Learning.”
3. Z. Wang, T. Jian, K. Chowdhury, Y. Wang, J. Dy, and S. Ioannidis, “Learn-prune-share for lifelong learning,” in Proceedings - IEEE International Conference on Data Mining, ICDM, Institute of Electrical and Electronics Engineers Inc., Nov. 2020, pp. 641–650. doi: 10.1109/ICDM50108.2020.00073.
4. G. I. Parisi, R. Kemker, J. L. Part, C. Kanan, and S. Wermter, “Continual lifelong learning with neural networks: A review,” May 01, 2019, Elsevier Ltd. doi: 10.1016/j.neunet.2019.01.012.
5. IROS 2016 : 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems : October 9-14, 2016, Daejeon Convention Center, Daejeon, Korea. IEEE, 2016.
6. Muñoz-Martín, S. Bianchi, G. Pedretti, O. Melnic, S. Ambrogio, and D. Ielmini, “Unsupervised Learning to Overcome Catastrophic Forgetting in Neural Networks,” IEEE Journal on Exploratory Solid-State Computational Devices and Circuits, vol. 5, no. 1, pp. 58–66, Jun. 2019, doi: 10.1109/JXCDC.2019.2911135.
7. D. Roy, P. Panda, and K. Roy, “Tree-CNN: A hierarchical Deep Convolutional Neural Network for incremental learning,” Neural Networks, vol. 121, pp. 148–160, Jan. 2020, doi: 10.1016/j.neunet.2019.09.010.
8. J. Zhang et al., “Class-incremental Learning via Deep Model Consolidation.”
9. G. I. Parisi, J. Tani, C. Weber, and S. Wermter, “Lifelong learning of human actions with deep neural network self-organization,” Neural Networks, vol. 96, pp. 137–149, Dec. 2017, doi: 10.1016/j.neunet.2017.09.001.
10. C. Wiwatcharakoses and D. Berrar, “SOINN+, a Self-Organizing Incremental Neural Network for Unsupervised Learning from Noisy Data Streams,” Expert Syst Appl, vol. 143, Apr. 2020, doi: 10.1016/j.eswa.2019.113069.
11. T. Flesch, J. Balaguer, R. Dekker, H. Nili, and C. Summerfield, “Comparing continual task learning in minds and machines,” Proc Natl Acad Sci U S A, vol. 115, no. 44, pp. E10313–E10322, Oct. 2018, doi: 10.1073/pnas.1800755115.
12. V. Lomonaco and D. Maltoni, “CORe50: a New Dataset and Benchmark for Continuous Object Recognition.” [Online]. Available: http://vlomonaco.github.io/core50
13. J. Kirkpatrick et al., “Overcoming catastrophic forgetting in neural networks,” Proc Natl Acad Sci U S A, vol. 114, no. 13, pp. 3521–3526, Mar. 2017, doi: 10.1073/pnas.1611835114.
14. R. C. O'Reilly, R. Bhattacharyya, M. D. Howard, and N. Ketz, “Complementary learning systems,” Cogn Sci, vol. 38, no. 6, pp. 1229–1248, 2014, doi: 10.1111/j.1551-6709.2011.01214.x.
15. A. Rusu et al., “Progressive Neural Networks,” Jun. 2016, [Online]. Available: http://arxiv.org/abs/1606.04671
16. D. Lopez-Paz and M. ' A. Ranzato, “Gradient Episodic Memory for Continual Learning.” [Online]. Available: https://github.com/
17. Y. Luo, L. Yin, W. Bai, and K. Mao, “An appraisal of incremental learning methods,” Nov. 01, 2020, MDPI AG. doi: 10.3390/e22111190.

18. D. Jirak, S. Tietz, H. Ali, and S. Wermter, "Echo State Networks and Long Short-Term Memory for Continuous Gesture Recognition: a Comparative Study," Cognit Comput, vol. 15, no. 5, pp. 1427–1439, Sep. 2023, doi: 10.1007/s12559-020-09754-0.
19. F. M. Castro, M. J. Marín-Jiménez, N. Guil, C. Schmid, and K. Alahari, "End-to-End Incremental Learning."
20. L. Mici, G. I. Parisi, and S. Wermter, "A self-organizing neural network architecture for learning human-object interactions," Neurocomputing, vol. 307, pp. 14–24, Sep. 2018, doi: 10.1016/j.neucom.2018.04.015.
21. G. I. Parisi, J. Tani, C. Weber, and S. Wermter, "Lifelong learning of spatiotemporal representations with dual-memory recurrent self-organization," Front Neurorobot, vol. 12, no. November, Nov. 2018, doi: 10.3389/fnbot.2018.00078.
22. C. Schüldt, I. Laptev, and B. Caputo, "Recognizing Human Actions: A Local SVM Approach *."
23. W. H. Chin, N. Kubota, C. Kiong Loo, Z. Ju, and H. Liu, "Spatial Map Learning with Self-Organizing Adaptive Recurrent Incremental Network."