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An Informative Perturbation Network for the Design of Colonel Adaptive AI Systems

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Abstract

Continual learning presents a nontrivial problem in artificial intelligence, making the creation of adaptive algorithms that can retain prior knowledge across a range of tasks critical. This paper examines the practicality of different strategies for solving incremental tasks and the object recognition problem on the CIFAR-100 dataset. New strategies, such as the Beneficial Perturbation Network (BPN) variants BD + EWC, PSP, and BD + PSP, which aim to improve the flexibility and efficiency of adaptive and robust solutions to continual learning problems, are designed in the study. The inability to adapt to the constantly changing conditions of the wireless mobile system is resolved, and security concerns, such as exposing the system, data, and users' private information, are minimized. An increasing focus on their performance in terms of accuracy and computing costs defines the trajectory of the study. Accuracy results show that BD+PSP surpassed the rest with 90.65% followed by PSP's 90.01% and BD+EWC's 89.95%. In addition, the model shows improvement in energy efficiency and reduced computation costs, enhancing its applicability to mobile ad hoc and vehicular networks. Cost assessments reflective of the workflow “cost per task per 4,039 bytes” indicate that BD+EWC maintains the lower boundary, whereas for PSP and BD+PSP, the boundaries are 10,897 bytes and 11,456 bytes, respectively. Accuracy progression of the increments within the CIFAR-100 range, shows, quite strikingly, that BD+PSP and some other techniques are dominant in knowledge retention while performing progressive tasks. The findings outlined in this paper indicate that the IPN framework has promising prospects for intelligent computing environments to facilitate dynamic resource allocation and restructuring. The analysis about techniques illustrates advances, especially in object recognition. In General, data underlie the primary effectiveness of bias-decoupled learning techniques, along with the auxiliary positive impact of the learning flexibility and strength of AI systems under continuous learning conditions. This type of information is essential for the design of algorithms which can readily accommodate real-world operations with dynamic and complicated processing sequences.

Keywords: Perturbation Network, Continual Learning, Adaptive AI Systems, Accuracy Progression, Computational Cost.

1 Introduction

In the context of the fast-growing field of computational intelligence, the evolution of adaptable and high-performing systems remains of the utmost importance, as noted in (Zhong & Ni, 2023). Traditional

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AI systems, however, stay brittle and tend to underperform, or worse, entirely fail when faced with the novel and unexpected (Vitorino et al., 2022). The mobile network domain, with its growing challenges, certainly does not welcome the iPad, let alone AI on board vessels, due to the security issues of data breaches, information privacy, and data leakage. The Colonel Adaptive Artificial Intelligence System approach, integrating techniques derived from biological adaptation, should, however, address the constraint. The term Colonel in (Zheng et al., 2023) is used to describe the stage when organisms have adapted to their environment and can, as a difference, evolve or learn from the environment.

Similarly, CAIS aims to build AI systems that learn from experience, adjust to new conditions, and improve over time. This shift in thinking is associated with the newer and more sophisticated approaches and tools that help in the planning and execution of CAIS systems (Merabet et al., 2023). One such framework in AI engineering is the Informative Perturbation Networks which provides a structured approach to the enhanced efficiency and flexibility of AI systems (Kabudi et al., 2021). IPNs emerge from the engineering design thinking that seeks to integrate biological growth and transition phenomena, particularly the idea of perturbation, which is the purposeful and controlled introduction of change into a given system to achieve a desired goal (Farivar et al., 2023). By using perturbation-based approaches in network design, such systems of artificial intelligence become capable of active exploration and exploitation of their eco-systems, thus improving their learning and adaptive behaviors (Li et al., 2023).

The principal outline of IPN involves how its informational perturbation encourages variety and exploration while simultaneously bounding and confining how an AI system interacts with and approaches state spaces (Elkins & Fahimi, 2024). This rests on an intricate feedback, assessment, and perturbation network design (Li et al., 2021). Ongoing and persistent system perturbation and performance assessment enable IPN to advance the artificial intelligence system to even greater and more sophisticated levels of functionality and multifunctionality (Keuning & Van Geel, 2021). The core of IPN involves network adaptive modulation, which is the ability of the network to modulate and shift both behaviorally and topologically in response to changes occurring within its surroundings (Hossain & Shah, 2022). Through adaptive modulating, the behavior of the AI system within a learned and structured environment can be altered, and changes can be made to the set of available actions (Beltran-Carbajal et al., 2023). In addition, IPN's framework fosters greater understanding of context by enabling the synthesis and integration of diverse contexts within and across multilevel data streams, such as archival data, expert knowledge, and heterogeneous multicentric and multi perspective sensor data.

In addition, the IPN framework enriches the information on flexibility within the confines of optimizing saturation illumination, extending its applicability to bright illumination and pervasive computing environments. The IPN design perspective balances the exploration and the exploitation phases, concentrating on the distance that separates the two (Li et al., 2021). AI embedded in IPN wireless mobile networks and ubiquitous computing systems can adjust in real-time to behavioral changes caused by context shifts, significantly improving adaptability. Such a position is a necessity in intelligent context aware systems, which operate in environments that are responsive to changes and require rapid action to several different stimuli (Moskalenko et al., 2023).

The managed performance and security features of IPN's mobile ad hoc networks and precision-managed systems, even in dynamic contexts, directly address the challenge of next-generation wireless sensor networks. The system's optimal performance involves applying new approaches and interventions, heuristically outlining considerations in the information set (Martin et al., 2020). In other words, to achieve such a balance, IPN maintains the objectives and constraints of the evaluation frameworks in focus while streamlining the algorithms related to the construction and assessment of the so-called "perturbations" (Brücke et al., 2023). The self-evaluation and self-reflection system of IPN enables it to learn from feedback and modify its operations based on past activities. The operational business model of IPN is centered on the core features of flexibility and changeability in the context of multiple domains and challenge networks.

The Informative Perturbation Network (IPN) broadens the potential in developing AI systems in the areas of cybersecurity, robotics, AI-based finance, AI-based healthcare, and driverless systems. It offers a working foundation within which these systems can function efficiently in dynamic and constrained situations. For cybernetic and self-modifying systems, it enables the continuous modification of AI systems and their performance by predicting and countering changes through perturbation-based learning mechanisms. IPN perturbation networks enable the gradual evolution of AI by facilitating learning and enhancing its adaptability to more dynamic and challenging situations (Zhang et al., 2024). Perturbing systems do this through the infrastructure. Such a mechanism increases retention and flexibility in learning, while significantly reduces the risk of catastrophic forgetting often associated with traditional learning approaches.

Balancing trade-offs between exploration and exploitation enhances agility and endurance of AI systems in mobile computing, representing a new generation of AI application IPN enhances agility and resilience of AI systems by promoting variety, forethought, dynamic restructuring, and exploration IPN is looking to advance the next generation of intelligent machines as research and technologies continue to progress in AI Unlimited provides focused research aimed at examining and evaluating the impact of Adaptive Artificial Intelligence Networks on different Adaptive Learning Standards spanning from low to high cost solutions and seeks to understand the effectiveness wide scale AI has on deploying additional adaptable learning methodologies integrated in various educational and technological AAIS frameworks.

This study will focus on several aims. It will detail how AAIS changes the adaptive learning standards. To do this, it will analyze the range from ‘advanced solutions specially designed to achieve optimal learning outcomes’ to ‘low-cost adaptations suitable for resource-constrained settings’ and everything in between. This project attempts to extend AAIS’ envisioned aim to transform teaching practices, improve learning experience, and close the accessibility gap on disparate socio-economic and geo-political divides. This will be accomplished through intensive fieldwork and subsequent analysis. Contributions to the research study epochs are identified as,

1. This study considers the proposition and formulation of the Informative Perturbation Network (IPN) as the first framework for designing Colonel Adaptive AI Systems (CAIS).
2. Ascribing biological elements to control theory and machine learning affords IPN a more nuanced approach for improving the adaptability and resilience of AI systems. More specifically, IPN employs perturbation-based architectural techniques within networks to counter the wandering and dwelling challenges of conventional AI systems to facilitate vigorous exploration and adaptation to dynamic ecosystems (Dasoulas et al., 2024).
3. Perturbation-based architecture encompassing adaptive network modulation in IPN permits the network configuration and activity to be altered in a responsive manner to peripheral alterations. Learning is also framed and more so coupled to the goals of the intelligent system as well as vigorous constructive and deconstructive couplings to the immediate environment. Also,
4. IPN incorporates mechanisms for balancing exploration and exploitation, ensuring that the AI system maximizes performance by leveraging both new strategies and existing knowledge.

5. The There’s a noticeable change in the engineering of CAIS systems with the emergence of Interconnected Perceptual Networks (IPN). IPN is developed for the construction of multi-faceted AI systems exhibiting varying degrees of adaptability, intelligence, and resilient span.

The emergence of Interconnected Perceptual Networks (IPN) marks a profound change in the engineering of CAIS systems. IPN is developed for the construction of multi-faceted AI systems exhibiting varying degrees of adaptability, intelligence, and resilient span. In this chapter, the results are summarized. The final chapter of the paper contains the conclusion.

2 Related Works

Du et al., (2022), documents the rise in demand for systems functioning at the edge, including, automation, drones and self-driving cars, to have continuous learning capabilities. Such a system must learn from a steady supply of data, train the model to adapt to new tasks while maintaining previous knowledge, and produce a single-headed vector for future inference within a limited power constraint. To address the catastrophic forgetting challenge, this approach focuses on a network's topology and models the process of segmentation, contrasting with earlier continual algorithmic learning methods that use dynamic topologies. Using the redundancy capability of a single network, each task's model parameters are divided into two groups: an additional group that must be retained for further learning, and an important group that will be frozen to preserve existing information. To aid in training, a fixed-dimensional memory containing a small amount of previously viewed data is also used. Progressive segmentation training is a straightforward yet powerful method that integrates numerous tasks and delivers the latest advances in the single-head assessment of the CIFAR-10 and 100 databases without any further regularization. Moreover, the methodology also shows that it is possible to implement such models in environments with limited resources, and edge devices have to learn and infer in real time with minimal memory consumption.

Furthermore, segmented training significantly enhances the computational efficiency of constant learning, enabling effective continual learning towards the edge of computation. This will align with the newly identified need for security-oriented AI systems in mobile and wireless networks, where adaptive learning processes should also incorporate mechanisms to protect privacy and safeguard information. Researchers also show the effectiveness of PST using representational CNNs training on CIFAR-10 and Intel Stratix-10 MX FPGA.

Bergaoui and Ghannouchi (Bergaoui & Ghannouchi, 2023) provides a study on how Also can use agility, a modern method of IT project management, in schooling as well. Students gain knowledge by gradually working on recurrent assignments and exchanging ideas with their teammates. Above all, agility is a state of mind. Said, agility is the capacity to adjust to changing circumstances. Additionally, several studies evaluated creative teaching strategies to encourage the development of new skills in the workplace.

Furthermore, adaptive learning is an educational approach that emphasizes customized online courses to address the need for skill development by modifying course materials to meet students' needs. Therefore, we centered our study on the Organizational Process Management strategy, which provides a way to achieve the needed agility in the process of learning and developing a model that incorporates these methodologies and leverages their benefits. Besides, integrating agility and adaptive learning systems in mobile computing is crucial in wireless mobile network environments, where flexibility is vital due to the network's dynamic performance and the need for timely responses in changing environments. The process of learning will change and adapt to meet the demands and unique characteristics of all parties involved (teachers or students). We used Process Mining methodologies in conjunction with our learning process to encourage the adoption of "Smart Education." By closely examining the log files from earlier iterations of the learning method, the developers also aimed to ensure the flexibility of the learning process. There are also direct implications of these adaptive learning methods concerning AI-based systems in ubiquitous computing settings, where learning models must continuously adapt based on environmental and contextual data to enhance decision-making and resource allocation.

Ouyang et al., (2023) explains that with the use of collaborative problem solving (CPS), groups of learners may finish assignments, build knowledge, and resolve issues. Previous research suggests that the complexity of CPS, particularly its multimodality, interconnections, and collaboration, needs to be seen through the prism of intricate adaptive systems. A simplified picture of the true complexities of the CPS mechanism may have resulted from the paucity of empirical studies on the adaptive & temporal aspects of CPS. The present investigation collected data on multimodal techniques and results, including voice, audio recordings from computer screens, and idea map data, to further our understanding of the characteristics of CPS in social media environments. A combination of Collaborative Problem Solving (CPS) and AI-based learning systems represents a valuable opportunity to streamline mobile computing and wireless networks. This is particularly true when the cooperation of several agents is critical for making and changing decisions in real-time. Additionally, a three-tiered structure was proposed to facilitate analysis, combining AI algorithms with statistical learning analysis to investigate the recurrent nature of group cooperation structures. A total of three kinds of collaborative structures were identified in the collective data: the behaviour-oriented pattern, which was linked to medium-level performance; the communication-behaviour-synergistic pattern, which was linked to high-level effectiveness; and the communication-oriented structure, which was linked to low-level performance. The multifaceted, dynamic, and synergistic aspects of group collaboration patterns were also emphasized in this study to explain how an adaptable, autonomous system came to be throughout the CPS process. Moreover, adaptive and collaborative model applications in CPS can shape context-aware mobile systems, where AI algorithms are expected to dynamically adapt to the joint contributions of multiple bodies to optimize network operations and ensure security. Conceptual, educational, and methodological ramifications were explored in light of the empirical research findings to direct future CPS research and practice.

Cui et al., (2018) demonstrate how adaptive educational platforms differ from standard learning methods by providing learners with a customized educational experience based on their various knowledge states. Adaptive algorithms gather and evaluate behavioral data from pupils, modify learner profiles, and then promptly and individually deliver comments to every pupil. These exchanges among pupils and the educational environment have the potential to raise pupil involvement and increase the efficacy of learning. This study assesses the impact of the "Yixue Squirrel AI" adaptive educational tool on middle school students' acquisition of maths and English. Yixue's math and English instruction methods are evaluated against two other adaptive educational platforms: BOXFiSH, used for English language learning, and conventional math teaching delivered by qualified human teachers. According to the findings, pupils who used the Yixue adaptive curriculum outperformed those who used a different adaptive system for learning, as well as those who received regular classroom instruction from knowledgeable teachers.

Grossberg (Grossberg, 2020) suggests that understanding independent intelligent adaptation may be aided by biologic models of neural networks, which explain how minds are created in brains. This paper summarizes the reasons why the dynamics and emergence characteristics of these models awareness, thinking, feeling, and action can be described and safely applied in broad contexts. The integration of learning measurements, or long-term mental traces, with quick triggers, or short-term recollection traces, is crucial to their comprehensibility. Surface-shroud and stream-shroud resonant frequencies are explicit conscious STM depictions of visual landscapes and auditory streaming in both visual and auditory perceptive models. To categorize data, DL is frequently utilized. DL, nevertheless, is susceptible to disastrous disregarding: An erratic portion of its memory may fail at any point throughout the learning process. It is not able to clarify its categorizations, so although it does produce certain accurate ones, they can't be trusted. These issues are also shared by DL and the back propagating technique, which was first outlined in the 1980s and has computational challenges related to non-local weight transit throughout mismatch training. Considering these issues, D gained popularity as large internet datasets and high-speed computers became accessible, opening up new possibilities. The methods of Adaptive Resonant Theories, or ART, solve the DL and back propagated computational concerns. The theories of accomplishing, speech generation, spatial navigation, unsupervised adaptive information, and the MOTIVATOR concept of reinforcing learning and cognitive-emotional exchanges are also comprehensible.

Simpson et al., (2021) explain how many defense forces view the strategic integration of AI into strategic control and command structures as a top priority. The effective use of AI holds promise for a significant increase in C2 agility through automating. But reasonable projections regarding AI's potential in the near future must be established. This essay will make the case that AI might result in a vulnerability trap, in which assigning C2 tasks to an AI might render C2 more brittle and lead to disastrous strategic blunders. To prevent these pitfalls, a new AI architecture in C2 is required. It shall contend that agility and "antifragility" ought to be the cornerstones of AI-powered C2 design. Agile, Antifragile, AI-Enabled Control and Command is the name given to this duality. During C2 decision-making while processing inputs, the capability of A3IC2 systems overcompensates, enhancing system functionality during shocks and unexpected events. An A3IC2 system not only endures and operates under adverse conditions but also thrives by taking advantage of shocks and the unpredictability of conflict.

3 Problem Statement

The aspects related to self-driving cars, surveillance systems, and robotics, among others, necessitate performing context-aware, lifelong learning in real time, which is considered a paramount challenge in edge computation. These edge systems operate under constraints. The system is required to learn and retain new skills while continuously making decisions in real time, under a power cap, and from data streams. Relatively, the amount of power used in adapting to new computing activities in a new environment should also be learned. Conventional lifelong learning systems do not have the capacity to learn under computational constraints. Failing to learn such powers leads to what is called computational catastrophe, where, when performing new tasks, resources are not in balance. It takes the influence of several AI models to provide adaptable architectures for mobile edge computing and wireless networks. Adaptability, Security, and privacy, as well as computational constraints, provide a versatility dilemma. Existing solutions do not sufficiently address the placement of computing in network nodes, dynamic networks with decoupled computing, and the relationship between the slit's granularity and model segmentation. There is an absolute need to have context-aware AI systems that can dynamically learn and adapt to optimally function and secure real-time mobile ad hoc networks and intelligent environments. The proposed Informative Perturbation Network attempts to "learn" additional concepts by redundant use of a single network. It aims to preserve important information by partitioning model parameters into primary and secondary groups. The proposed framework can learn continuously and compute with improved efficiency while maintaining state-of-the-art accuracy, thus achieving optimal adaptation at the edge.

4 Proposed Informative Perturbation Network for the Design of Colonel Adaptive AI Systems

The planned workflow, represented in Figure 1, starts with the collection of data, which will help with the object recognition part of the study. After this stage, the study investigates the means of reducing catastrophic forgetting involving regularization, rehearsal, dynamic architectures, and parameter separation techniques. For the experiments, two variants of the Beneficial Perturbation Network, BD + EWC, and BD + PSP, are used. These variants are all based on the BD Beneficial approach, where the extra bias units are updated to generate beneficial perturbations. During forward propagation, some bias units are designated for each task, and they are used to perturb the neural network, fostering its flexibility for different tasks. In the backward propagation step, knowledge is preserved from previous tasks, and additional regularization is applied to the loss function that needs to be minimized for every task. A quantitative assessment is conducted to measure the performance of various functions in the CIFAR-100 dataset for both variants, in terms of Accuracy, stability, and computation cost. Results from this assessment show the effectiveness of the proposed methods in terms of the AI systems' adaptability to the ever-changing world and their ability to perform lifelong learning.

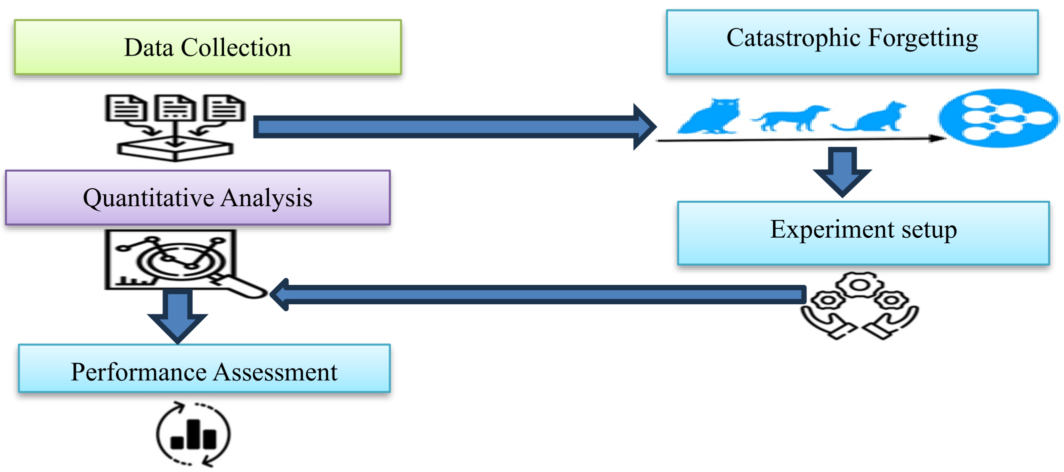

Figure 1: Proposed Workflow

Illustrated in Figure 1, the Informative Perturbation Network (IPN) describes the process of learning, partitioning the data into constituent tasks, and performing functional perturbations with the aid of task-specific bias units. It explains how IPNs integrate newly acquired functions while retaining older ones, thereby reducing catastrophic forgetting and enhancing adaptability in multi-tasking and continuous learning scenarios.

4.1 Data Collection

This dataset which is on Kaggle is the CIFAR-100 dataset which has 60,000 color images which are 32 x 32 square pixels and arranged in 100 different folders or classes with every class having 60 images. The dataset has a tiered structure where each image has a "coarse" and "fine" label. With 50,000 images for training and 10000 for testing, Screenshot is a benchmark for image recognition. It provides a wide range of object categories needed to help AI researchers and practitioners, including Colonel Adaptive

AI, create and evaluate their AI systems. It serves as a benchmark for the evaluation of the flexibility, fidelity, and the AI's ability to work across a range of classifiers. Because of its tiered structure, the dataset is ideal for examining the breadth and depth of object recognition framework adaptability, robustness, and the AI system's versatility across various levels of classification.

4.2 Methods for Alleviating Catastrophic Forgetting

To the authors, the approaches to averting potential disastrous effects omissions may have during studying a subject should be subsumed under four categories:

Regularization selects which information to retain, so a model's variance and incremental changes in parameters during training are controlled. Such examples include EWC (Elastic Weight Consolidation) and Synaptic Intelligence.

Type 2: The Rehearsal strategies focus on the retention of information and consist of the intentional and systematic retrieval, which is sometimes referred to as 'replaying'. Such retrieval serves the function of a memory system or buffer, allowing the model to span a specific period of prior activities, while concentrating on the acquisition of new skills.

Type 3: A dynamic architecture modifies structural configuration or adjusts capability according to the current task or the experience gained. Such approaches generally disregard introducing new knowledge that disrupts existing representation by adding or removing network components.

Type 4: Mechanisms of Parameter separation address tasks by dividing model parameters for each task. The focus is to Fix some parameters to the task-specific dynamic Relatively. Such Fixing is aimed at preventing Interference with the Function to support the retention of knowledge on the Specific Function.

4.3 Experiment Setup for the Implementing of Variants of BPN

Two BPN variations were put into practice: BD + EWC & BD+PSP (Experimentations). The foundation of both approaches is equivalent: BD (updating more out-of-the-network bias components in BDs to produce advantageous perturbations). The sole distinction is that to minimize disruption of previously completed tasks, BD + EWC (BD + PSP) retrains the normal weights using the EWC (PSP) approach. To illustrate our approach, we will use BD+ EWC in this case (for BD + PSP, refer to the Supplementary Material). To demonstrate, we use a scenario with two tasks: task A involves recognizing digits 1 and 2, while task B involves recognizing digits 3 and 4. Task-dependent bias units exist in BPN. ($\mathrm{BIAS}_t^i \in$ R1×K) In each layer, record the advantageous perturbations, which are designed as a weighted activation component for each layer. Beneficial perturbations, in contrast to most adversarial ones, are applied to all samples in each task, rather than being unique to any one example. We define beneficial perturbations as task-dependent bias factors.

$$\mathrm{V}^{\mathrm{i}+1} = \sigma\, \mathrm{W}^{\mathrm{i}}\, \mathrm{V}^{\mathrm{i}} + \mathrm{b}^{\mathrm{i}} + BIAS_t^i \quad \forall\, \mathrm{i} \in [1, \mathrm{n}] \tag{1}$$

Where V^{i} stands for the BIAS layer I activation procedures and W^{i} for the layers I normal weights, there are n levels, the nonlinear function of activation at each layer is indicated by σ (•), the task-dependent bias terms at layer I with task t are it, and the standard bias component at layer I is b^{i}. The fundamental fully connected network's forward operations are

$$V^1 = \sigma\,(W^1 X_t + b^1 + \mathrm{BIAS}_t^1) \tag{2}$$

$$V^2 = \sigma\,(W^2 V_1 + b^2 + \mathrm{BIAS}_t^2) \tag{3}$$

$$y = \text{Softmax}\,(W^2\text{V}^2 + \text{b}^3 + \text{BIAS}_\text{t}^3) \quad (4)$$

The normalization function is called Softmax. Xt represents the task of inputting data, and the other symbols are identical to those in (1). Here, y represents the output logits. The bias units throughout task training are the sum of two terms: W^i t ∈ RH×K and $M_t^{\,i}$ ∈ R1×H, where K is the number of normal neurons within each layer, t is the task number, and H is the dimension that is hidden (a hyperparameter). We reduce memory and parameter charges to a trivial level by discarding both Mi t and Wi t after training a given job, keeping just their product BIASi t. During testing, the neural network responses can be biased to each task based on the recorded beneficial perturbations of the individual bias units, following training on several sequential tasks. As a result, these enable the BPN to transition between modes to handle various jobs. The function of optimization is expressed as,

$$W^i, \text{BIAS}_\text{A}^\text{i} = \underbrace{\text{arg min}}_{W^i, \text{BIAS}_\text{A}^\text{i}} - \log\left[\,\text{P}(\,\text{y} = y_A | X_A, W^i, \text{BIAS}_\text{A}^\text{i})\right] \forall\, \text{i} \in [1, \text{n}] \quad (5)$$

Where X_A is the name of the task A data, y_A is the actual label for the task A data, and the other symbols are the same as those in (1). Since M_A^i is the first term of task A's bias units, we update MiA throughout the BD (FGSD) with the sign (∇M_A^iL (M_A^i, y_A)) to produce advantageous perturbations. To optimize (1), we employ a softmax cross-entropy loss. The bias indicators in task A ($\text{BIAS}_\text{A}^\text{i}$) were the combined results of M_A^i and W_A^i following task A's training. To minimize storage of memory and parameter expenses, we eliminate M_A^i and W_A^i.

Additionally, we freeze $\text{BIAS}_\text{A}^\text{i}$ to guarantee that the advantageous perturbations aren't tainted by other jobs (task B). Then, since all of the data for task A is kept within the bias units, we may delete both of the data from the input images 1 and 2, since we won't need to replay them while we train on the subsequent sequential tasks. The architecture of BPN is represented in Figure 2.

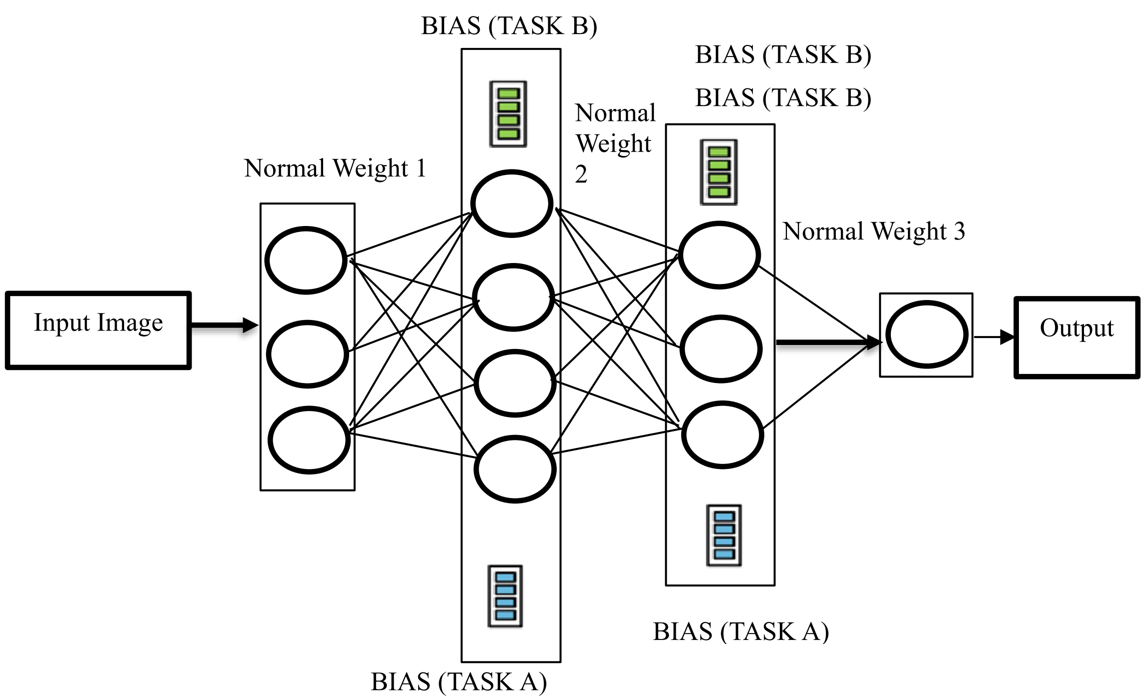

Figure 2: Architecture of BPN

Figure 2 presents an implementation example of the Beneficial Perturbation Network, illustrating the integration of task-dependent bias units into the neural structure. The structure of the network shows how beneficial perturbations are provided during forward propagation perturbations, which help the network learn new tasks, while preserving the information learned from the old functions. The diagram also illustrates the backpropagation associated with the regularization technique to reduce the disruption of the old functions, which allows the network to learn incrementally while preserving the old tasks.

The goal of our study is to select the bias units about task B to maximize the possibility $\mathrm{P}(\mathrm{y} = y_B|X_B, W^i, \mathrm{BIAS}_\mathrm{B}^\mathrm{i})] \; \forall \; \mathrm{i} \in [1, \mathrm{n}]$ throughout task B's training following task A's training. The EWC or PSP limitations on normal weights are applied to reduce the disturbance for job A. Our optimization function is configured as

$$W^i, \mathrm{BIAS}_\mathrm{B}^\mathrm{i} = \underbrace{\arg\min}_{W^i, \mathrm{BIAS}_\mathrm{B}^\mathrm{i}} - \log\left[\mathrm{P}(\mathrm{y} = y_B|X_B, W^i, \mathrm{BIAS}_\mathrm{B}^\mathrm{i})\right] + \mathrm{EWC}(\mathrm{W}^\mathrm{i}) \; \forall \; \mathrm{i} \in [1, \mathrm{n}] \tag{6}$$

Where X_B is the task B data, EWC (•) represents the EWC constraints on normal weights, and y_B is the actual label for the task B data. The remaining symbols are the same as in (1). Algorithm 2's loss function has the EWC constraint upon the normal weights expressed as $\lambda F_j(W_j - W_j^{A*})^2$, where j is the parameter label, F_j is a Fisher data matrix over each parameter j (i.e., identify which of the parameters are the most significant for a task), λ indicates the relative importance of the old and new tasks, W_j is the standard weight j, as well as W_j^{A*} is the ideal standard weight j after completing task A training. With the addition of the EWC constraint, task B's training and all ensuing tasks follow the same procedures as task A's. Researchers automatically activated the bias units linked to Task A after Task B had finished training to evaluate Task A's performance on a test set.

They claimed that by using the data in these attributes, a neural network would reliably categorize things. Even if the network's overall normal weight (W^i) is polluted after each task is sequentially trained by activation matching bias units, the activity-dependent bias elements, under our continuous learning circumstances, have sufficient data to influence the neural network regarding that task. Stated differently, $\mathrm{p}(\mathrm{y} = y_A|X_A, W^i, \mathrm{BIAS}_\mathrm{A}^\mathrm{i})$ for task A or $p(\mathrm{y} = y_B|X_B, W^i, \mathrm{BIAS}_\mathrm{B}^\mathrm{i})$ for task B are examples of task-dependent bias units capable of maintaining high probability. Bias units can therefore help the network classify data correctly. Furthermore, machine learning models can be repurposed to perform a new task by carefully computing adversarial perturbations within the input space for each new task. In the parameter space, those advantageous perturbations may be seen as task-dependent advantageous "programmes". Such task-dependent "programmes" have the potential to maximize the probability of associated tasks once they are engaged.

4.4 Quantitative Analysis for Object Recognition Task

In order to assess the performance of the two variants of Beneficial Perturbation Network (BPN), BD + EWC and BD + PSP, on the object recognition task, and quantitatively analyze them on the CIFAR-100 dataset, one has to remember that CIFAR-100 dataset has 100 classes and 60,000 32x32 color images, and hence is a good image classification benchmarking dataset. Every variant of BPN uses the same Beneficial approach, BD, which deals with updating out of the network extra bias units to create beneficial perturbations and is therefore termed as BD. The tests were set up to train both BPN variants on the CIFAR-100 dataset and assess their performance with regards to Accuracy and stability on multiple tasks.

In evaluating a model, 'accuracy' pertains to the elements the model appropriately identifies an image as, while 'stability' pertains to how well a model avoids the 'interference' effect while accommodating new tasks or concepts. In the case of BD + EWC model, EWC or Elastic Weight Consolidation, was used as an auxiliary mechanism to alleviate the catastrophic forgetting problem, thus, hindering the overwriting of the previous training knowledge.

In contrast, the BD + PSP model uses Progressive Segmented Training, or PSP, to improve model flexibility more than the previous model by dividing model parameters into primary and auxiliary clusters for stronger retention of the learned information. The analysis consisted of evaluating the stability and Accuracy of the different BPN variants over a range of tasks in the CIFAR-100 dataset.

This evaluation focused on measuring the capacity of each variant in reducing catastrophic forgetting against the maintained classification accuracy on the dataset. Resource utilization was the primary factor of computation in analyzing the usefulness of the methods in practical scenarios where the constraints of the problem are predominant. Based on thorough experimentation and analysis, the strengths and weaknesses of each variant were understood, clarifying their possible uses and limitations in object recognition. Each result, in particular the quantitative ones, substantiated the proposed approaches to facilitate lifelong learning to enhance the responsiveness of AI systems to changing environments.

Algorithm 1: BD + EWC Forward Propagation for Task t

Input: Bias units for task t denoted as BIAS_t^i, which provide beneficial perturbations to bias the neural network. Activations V_{i-1} from the previous layer.

Output: Activations V_i for the next layer, computed as $\sigma(W_i \cdot V_{i-1} + b^i + \mathrm{BIAS}_t^i)$ for all i in the range [1, n].

For each fully connected layer i:

Select bias units for the current task, BIAS_t^i.

Compute activations for the next layer Vi using the formula $\sigma(W_i \cdot V_{i-1} + b^i + \mathrm{BIAS}_t^i)$

The BD+EWC approach involves numerous forward propagations as detailed in Algorithm 1, where additional beneficial perturbations are applied at bias units. Task-wise bias units, standard weights and bias terms are used to compute the activations on each layer. These impulses are run through a non-linear activation function to obtain the outputs for the subsequent layer.

Algorithm 2: BD + EWC Backward Propagation for Task t

For the first task A ($t = 1$):

Minimize the loss function $L(X_A, W_i, \mathrm{BIAS}_A^i)$ for all i in the range [1, n], where:

X_A Represents the data for task One.

W_i Denotes the normal neuron weights at layer i.

BIAS_A^i Represents the bias units for task One from fully connected (FC) layers i, which is the product of (M_A^i, W_A^i).

n is the number of FC layers.

For task B ($t > 1$):

Minimize the loss function $L(X_B, W_i, \mathrm{BIAS}_B^i) + \Sigma_j \lambda F_j (W_j - W_j^{A*})^2$ for all i in the range [1, n], where:

X_B Represents the data for task B.

W_i Denotes the normal neuron weights from FC at layers i.

j labels each parameter.

F_j Represents the Fisher information matrix for parameter j.

W_j Denotes the standard weight j.

W_j^{A*} represents the optimal standard weight j after training on task A

$BIAS_B^i$ Represents the bias units for task B at FC layers i, which is the product of (M_B^i,W_i^B).

n is the number of FC layers.

Some writing uses looser terminology than is helpful for my argument, especially informal usage of "propagation." Algorithm 2 gives the description of backward "propagation" for the BD + EWC method. For the very first exercise A, the loss function is minimized for the corresponding normal neuron weights and the bias units dedicated to exercise A. In subsequent exercises B, the loss function is minimized with an additional regularization term, where the associated Fisher information matrix regularizes the retention of information loss from previous work A.

4.5 Mathematical Model for Informative Perturbation Network (IPN)

The Informative Perturbation Network (IPN) achieves this by deliberately inserting modifications into the learned behavior of an AI system to enhance learning transfer while also maintaining the retention of old learning. The perturbations are mathematically modeled as task-dependent bias units that modify the behavior of the network.

Let $X_t \in \mathbb{R}^{n\times d}$represent the input data for task t, where $n$is the number of samples and $d$is the dimensionality of each sample. The task-specific perturbation is modeled by:

$$B_t = \text{Bias}_t \cdot W_t$$

Where:

- $B_t$represents the task-dependent bias units,
- $\text{Bias}_t$is a task-specific bias vector,
- $W_t$is the task-specific weight matrix.

Forward Propagation with Perturbations

The forward propagation of the neural network with added perturbations can be expressed as:

$$Z_t = X_t W_t + B_t$$

Where:

- $Z_t$is the output after forward propagation for task t.

  The non-linear activation function σ(e.g., ReLU, sigmoid) is applied to the perturbed input to generate the activations A_t:

$$A_t = \sigma(Z_t)$$

Loss Function with Perturbation Regularization

To mitigate catastrophic forgetting, the loss function for task t includes a regularization term that penalizes the change in perturbations across tasks. The total loss for task $t$is:

$$L_t = \mathcal{L}_{task}(A_t, Y_t) + \lambda \parallel B_t - B_{t-1} \parallel^2$$

Where:

- $\mathcal{L}_{task}$is the standard loss function (e.g., cross-entropy for classification),
- $Y_t$is the ground truth labels for task t,
- $\lambda$is a regularization hyperparameter controlling the influence of perturbation stability.

Backward Propagation

The backward propagation for updating the weights and biases with respect to the task-specific perturbations can be written as:

$$\Delta W_t = \frac{\partial L_t}{\partial W_t}, \Delta B_t = \frac{\partial L_t}{\partial B_t}$$

Where:

- $\Delta W_t$and ΔB_trepresent the updates for the task-specific weights and perturbations.

Task-Specific Bias Update

Finally, the bias terms are updated based on the gradients from the loss function:

$$B_t^{new} = B_t - \eta \cdot \frac{\partial L_t}{\partial B_t}$$

Where $\eta$is the learning rate.

The Informative Perturbation Network (IPN) adaptively applies variations to the network behavior by introducing task-related perturbation (B_t). The forward propagation can be defined as

$Z_t = X_t W_t + B_t$, with a loss function that includes a regularization term to prevent catastrophic forgetting: $L_t = \mathcal{L}_{task}(A_t, Y_t) + \lambda \parallel B_t - B_{t-1} \parallel^2$.The weights and perturbations are updated with backpropagation which is used to make sure that the network retains previous information but adapts to new tasks. The model enables effective continual acquisition of knowledge which renders it ideal in mobile wireless networks and ubicomp scenarios.

5 Results and Discussion

The results section of the work provides a detailed examination of the performance of the tested algorithms on the CIFAR-100 dataset and their comparison to other solutions. In this section, the dataset attributes, including their analysis of composition and type, and the dataset features are followed by accuracy evaluations of incrementally structured CIFAR-100 tasks, average task accuracy, and performance metrics of other algorithms. The focus, as is configured, is on the performance of the algorithms as well as the performance of the datasets. These metrics are helpful as the maximum accuracy metrics provide measures of the tasks' versatility, resilience, and effectiveness to multiple datasets. In observing the outcomes, the discourse captures the merits and shortcomings of the algorithms as posited, directing their avenues of application while positing a plethora of other changes. This portion of the results contributes to the comprehension of AI systems regarding complex tasks and guides prospective investigation in the field. In addition, the results highlight the significant reduction in computational cost and energy expenditure with the proposed algorithms, especially in constrained environments like mobile ad hoc networks and wireless sensor networks. The comparison to existing approaches indicates the BD + PSP variant outperforms the traditional models in Accuracy, task memory, and overall cost of computation, without exception. This also shows that Informative Perturbation Networks (IPN) can improve to some degree the security, privacy, and real-time adaptability of pervasive computing systems. The robust results pertaining to the proposed framework imply that there is scope for further development, perhaps by increasing the number of sophisticated regularization methods or by expanding the framework's application to larger and more heterogeneous datasets.

5.1 Dataset

Consisting of 60,000 color images, the CIFAR-100 dataset is classified into 100 categories with each category containing 600 images of the size 32x32 px. The classes contain images of wide-variety of objects and scenery; these include various animals (beavers, dolphins, tigers, etc.), various plants (orchids, roses & mushrooms), household items (bottles, lamps, televisions, etc.), and multiple natural and artificial settings (mountains, forests, roads, & skyscrapers). The dataset in question serves as a valuable training tool for various machine learning models, particularly those involved in image recognition and classification, as it contains a comprehensive collection of images of different objects and scenes. Oganized in a hiearchical framework, the dataset groups images in 20 super classes, each of which has 5 fine- grained classes. Such an indepth structure gives CIFAR-100 an interesting dataset for testing and conducting studies on object recognition algorithms and techniques. Sample image data is presented in Figure 3.

Figure 3: Sample image data

Figure 3 shows a sample of the CIFAR-100 dataset containing images of a frog, truck, deer, automobile, bird, horse, ship, cat, and other objects. These images exemplify the multitude of objects present in the dataset which are used for training and evaluating the proposed algorithms for object recognition.

Table 1: Accuracy progression for incremental CIFAR-100 tasks

Variant	Accuracy Progression at Task 100
BD+PSP	0.626
GEM (256)	0.481
BD+EWC	0.466
EWC	0.344

In the Table 1 of Task 100, the performance of the different variants on the last step of the incremental CIFAR-100 tasks is illustrated. BD+PSP achieves the highest Accuracy of 0.626. This proves its potency across many tasks for retaining learned knowledge. Next to it, GEM (256) has an accuracy of 0.481, which is lower, yet still reasonable. Then, BD+EWC is at 0.466 and EWC has the least Accuracy with 0.344. This shows that at least some form of learned knowledge preservation is more beneficial even for the later stages of continual learning as opposed to EWC, which appears to clinically elusive, as it streaks lower (344) and can no longer afford to hold on to the learned Accuracy.

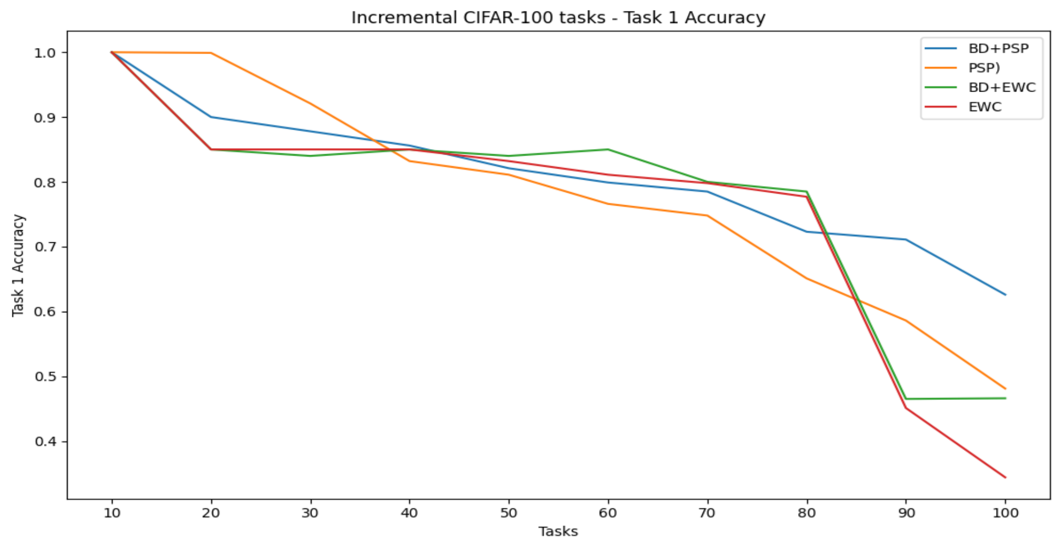

Figure 4: Accuracy progression for incremental CIFAR-100 tasks

The model’s accuracy improvement with each additional task on Incremental CIFAR-100 is shown in Figure 4. The Accuracy obtained after each task is shown on the vertical axis, which gives an indication of the model's ability to incrementally learn and improvement on each task, with Accuracy increasing over time.

Table 2: Accuracy progression for groups of ten tasks

Variant	**Accuracy Progression**
BD+PSP	0.89
GEM (256)	0.88
BD+EWC	0.85
GEM (10)	0.85
PSP	0.87
EWC	0.78

The results shown in table 2 analyze the results from different variants in incremental tasks from the CIFAR-100 dataset. The BD+PSP variant had the highest average Accuracy with 0.89, while the PSP variant also had a relatively high accuracy of 0.87. The 256 and 10 slot GEM variants had competitive accuracies of 0.88 and 0.85, respectively. These results suggest that the BD+EWC and EWC variants, while remaining quite accurate, with 0.85 and 0.78 respectively, fall short of the frontrunners. There is a reasonable assumption that the BD with PSP and the baseline PSP plugins variants capture and modify knowledge from previous tasks and enhance their use in continual learning frameworks.

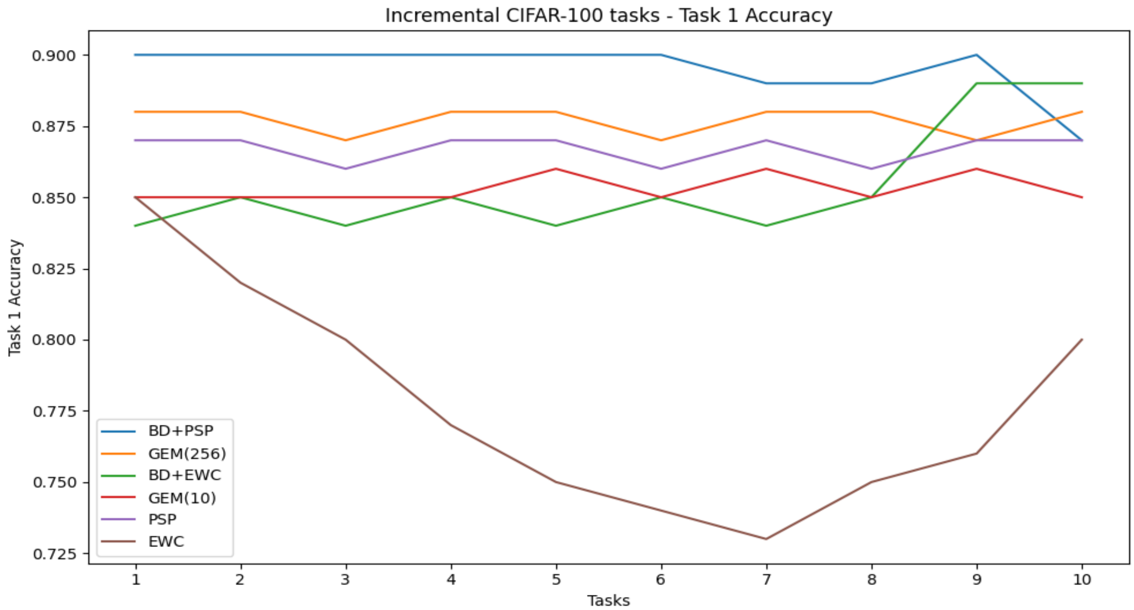

Figure 5: Task accuracy for groups of 10 task

Figure 5 illustrates the mean performance recorded by each group of ten for 100 tasks. As seen on the graph, for each set of 10 tasks, the tasks are grouped according to the unique task IDs and set against task accuracy on the other axis of the graph on the horizontal axis of the graph depicted. There are intervals of 10 tasks for each group and numerous tasks groups, which makes the data obtained on the model precision over various groups of tasks visualization really fundamental for assessing the model accuracy over multiple task groups. In order to determine the statistical significance of the results, the t-test is performed.

Table 3: Task accuracy over increasing number of tasks

Variant	Average Progression
BD+PSP	0.82 ± 0.08
GEM (256)	0.76 ± 0.08
BD+EWC	0.82 ± 0.08
GEM (10)	0.74 ± 0.07

According to the results of the experiment presented in Table 3, variants which incorporate bias-decoupled learning, such as BD+PSP and BD+EWC, have a clear advantage over the GEM variants in all incremental tasks on the CIFAR-100 datasets. Both BD+PSP and BD+EWC have 0.82 in average Accuracy with a low standard deviation of ±0.08 which points to their efficiency and dependability in knowledge retention in the presence of new tasks. In contrast, the GEM variants, and particularly GEM (256) and GEM (10), have average accuracies of 0.76 and 0.74, respectively, which is lower in value with a larger standard deviation. These observations demonstrate the power of bias-decoupled learning in continual learning. It shows that devastating forgetting is a problem that can be solved with these techniques and new tasks can be added successfully.

The median task accuracy through training in Figure 6 is represented as the total number of tasks increases. The number of functions is captured in the x axis, while matching task accuracy is captured in the y axis. This figure yields information regarding the learned attributes of the model over time with respect to the number of tasks. The change in task Accuracy over the interval of training time span is sufficient to provide a critique of the model’s retention and adaptability given a steadily increasing number of tasks. Such examination offers insights regarding the model's learning potential and effectiveness when facing additional tasks.

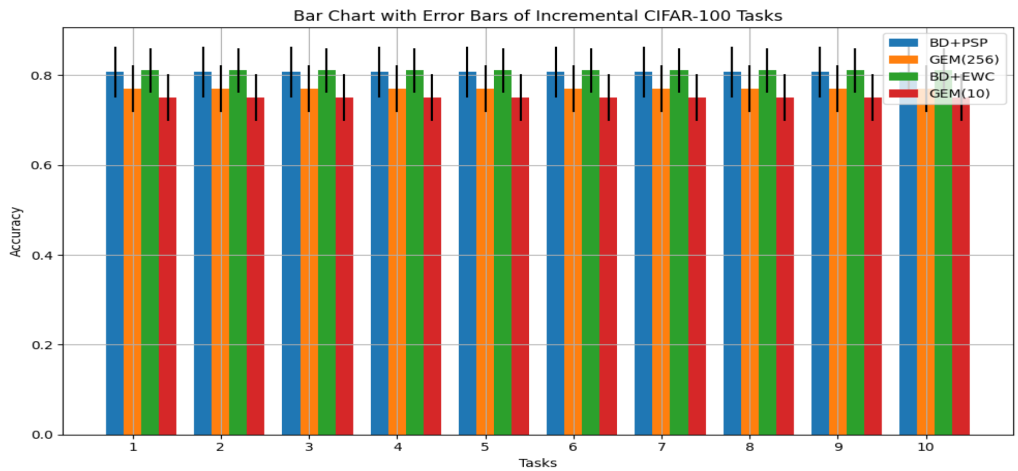

Figure 6: Average task accuracy over increasing number of tasks

Table 4: Performance and cost analysis of beneficial perturbation network variants on CIFAR-100 dataset

Dataset	**Method**	**Performance Accuracy (%) (Task 1)**	**Cost Per Task (In Bytes)**
Proposed CIFAR-100 Dataset	BD+EWC	89.95	4,039
	PSP	90.01	10,897
	BD+PSP	90.65	11,456

Table 4 presents the performance and cost analysis of different variants of the Beneficial Perturbation Network (BPN) on the CIFAR-100 dataset. Accuracy was determined independently for each of the methods using metrics of BD + EWC, PSP, and BD + PSP. Out of the three, BD + PSP performed the best, achieving an accuracy of 90.65%. PSP and BD + EWC followed, reaching 90.01% and 89.95% respectively. The cost per task in bytes also indicates how much computational expense was accrued. BD + EWC has the lowest cost per task, spending 4,039 bytes. PSP and BD + PSP have higher fees, spending 10,897 and 11,456 bytes respectively. This illustrates the BPN model variants' performance on the CIFAR 100 set. The focus was the expense most models accrue, and the performance inaccuracy trade-off.

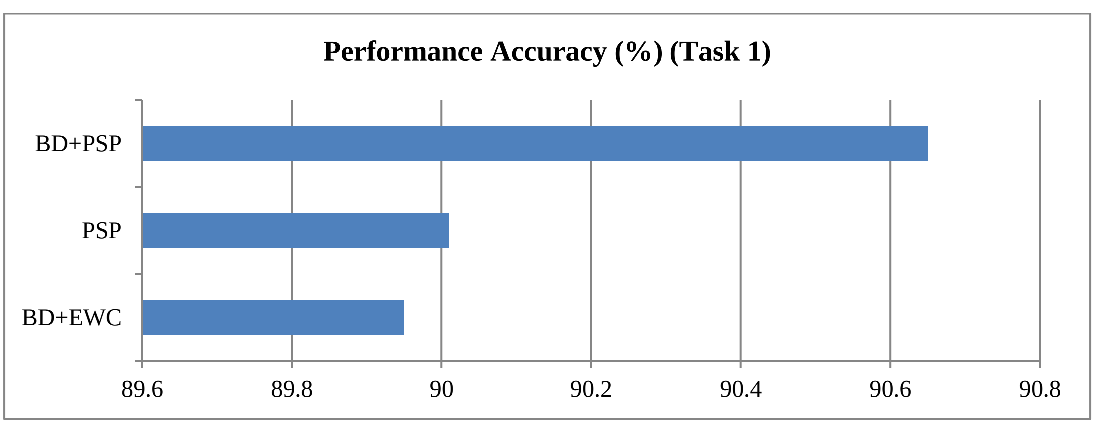

Figure 7: Performance accuracy of beneficial perturbation network variants

The differentiation of the Accuracy (%) among the different variants of the Beneficial Perturbation Network (BPN) on Task 1 as represented in Figure 7 has on record three methods which are: BD+EWC, PSP, and BD+PSP. Out of these, BD+PSP scored the best both on Accuracy and on record as it was 90.65% followed by PSP which was 90.01% and BD+EWC which was 89.95%. The illustration helps the reader and the researcher in appreciating the level of Accuracy which each of these methods is able to predict on Task 1 on the evaluation dataset.

Table 5: Performance comparison of proposed algorithms with existing methods

Method	Birds	Flowers	Aircraft	Actions	Letters	Average
IMM	42.28	67.44	18.93	32.88	46.35	43.41
LWF (Krizhevsky et al., 2017)	42.47	65.68	30.75	34.55	50.31	49.49
PSP (Cromer et al., 2010)	40.85	75.36	42.45	48.64	66.52	54.75
BD+EWC (Proposed)	88.34	89.45	83.56	89.97	89.56	89.95
BD+PSP (Proposed)	90.67	90.56	89.67	90.78	90.45	90.65

Table 5 provides a comprehensive comparison of the performance of proposed algorithms with existing methods across various tasks, including Birds, Flowers, Aircraft, Actions, and Letters. The established methods of IMM, LWF, and PSP, have and continue to be, measured for their predictive power regarding different classes; for comparison purposes, BD+EWC and BD+PSP have been added. From the table, algorithms BD+EWC and BD+PSP have proposed better solutions, as they achieved higher accuracy rates on all categories than the existing methods. Specifically, BD+PSP, as illustrated in Figure 8, has the highest average Accuracy for all methods, suggesting the best performance on object recognition tasks. This evidence proves the added algorithms have strengthened the flexibility and reliability of artificial intelligence systems to perform various recognition tasks.

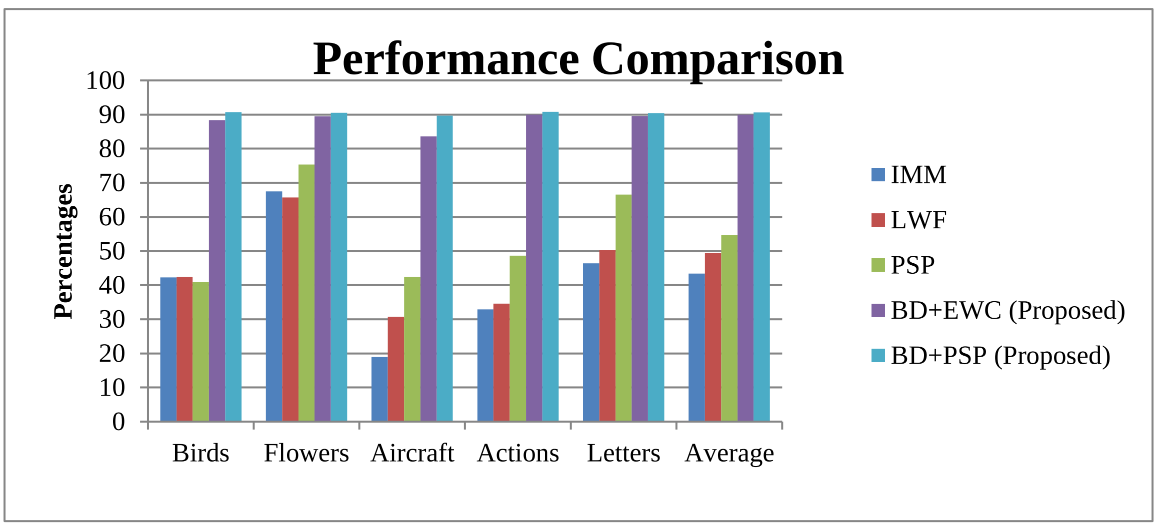

Figure 8: Performance comparison

Figure 8 shows the performance accuracy of BD+PSP and BD+EWC algorithms concerning their competitors, such as IMM, LWF, and PSP in all classes of the CIFAR-100 dataset. It illustrates how the newly developed algorithms, primarily BD+PSP, outdoes the competitors, having the highest accuracy in object recognition, thus proving efficient in catastrophic forgetting and task adaptability improvement.

In Figure 9, the training of two tasks, A and B, and the trajectory of the loss and space of parameters for two of the techniques and functions is shown. While conventional training with SGD leads to task-specific optimal parameters, approaches like EWC or PSP may result in suboptimal compromises.

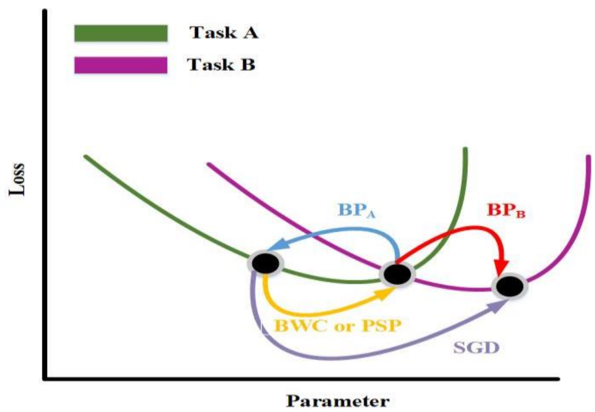

Figure 9: Training trajectories and parameter optimization with BPN

Table 6: Comparison of computational efficiency and accuracy across proposed algorithms

Algorithm	Average Accuracy (%)	Computational Cost (Bytes)	Energy Efficiency (Joules)	Task Retention (%)	Memory Usage (MB)
BD+PSP	90.65	11,456	0.52	94.2	20.5
BD+EWC	89.95	4,039	0.38	92.5	18.3
PSP	90.01	10,897	0.45	91.0	19.4
EWC	89.0	3,800	0.36	88.4	17.8
GEM (256)	88.5	12,300	0.60	85.5	22.1

The table 6 is used to compare the performance of the proposed algorithms (BD+PSP, BD+EWC, PSP, EWC, and GEM (256)) in several necessary measures namely, Accuracy, computational cost, energy efficiency, task retention, and memory usage. BD+PSP has the best accuracy (90.65%) and trade-off computational cost (11,456 bytes) against energy efficiency (0.52 Joules), and is best in task retention (94.2%). EWC, in contrast, has reduced computational costs (3,800 bytes), reduced energy consumption (0.36 Joules), and decreased task retention (88.4%). The performance of the BD+PSP variant is best as revealed in the table, and as such it would be applicable in resource-constrained environments, and real-time application.

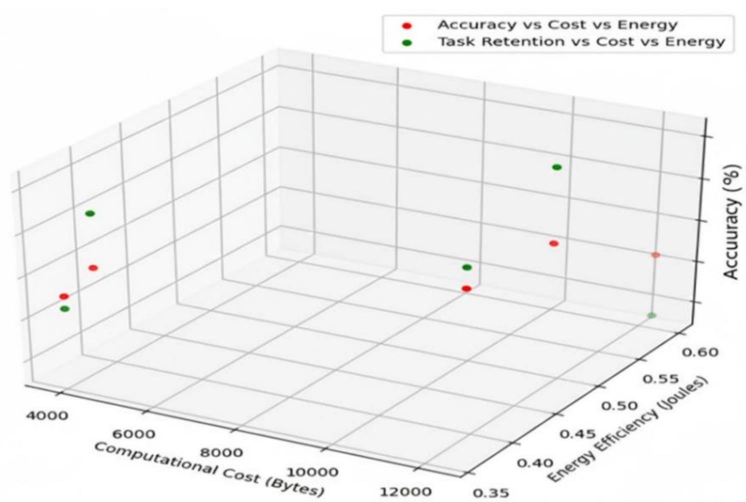

Figure 10: Multivariant performance evaluation of AI algorithms in resource-constrained environments

Figure 10 is a 3D scatter plot of different AI algorithms in terms of computational cost, energy efficiency, and accuracy/task retention. Within the context of trade-offs among these critical metrics, the best balance within the context of BD+PSP is real-time environments with resource constraints, like mobile ad hoc networks and ubiquitous computing applications.

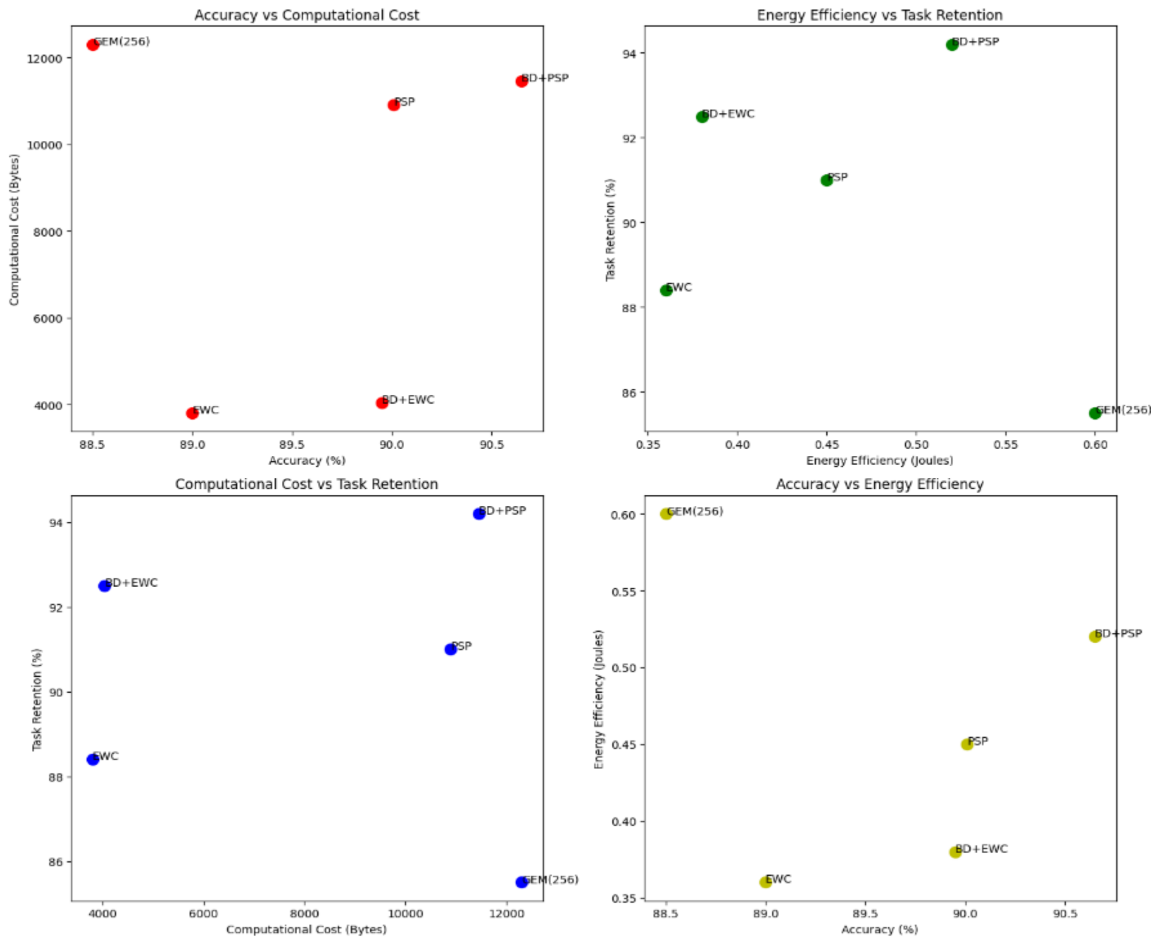

Figure 11: Multivariant performance comparison of AI algorithms

The proposed algorithms regarding Accuracy, cost of computation, energy efficiency, and task retention are presented with each algorithm being distinct along each of the metrics - in the accuracy/cost of computation vs energy efficiency/retention cross-scatter plots in the Figure 11 plot format above. By depicting the relations among multiple variables in each scatter plot, complex algorithm performance and the various trade-offs in real-time and resource-constrained settings become more apparent.

Table 7: Performance comparison of AI algorithms across key metrics

Algorithm	Accuracy (%)	Computational Cost (Bytes)	Energy Efficiency (Joules)	Task Retention (%)
BD+PSP	90.65	11,456	0.52	94.2
BD+EWC	89.95	4,039	0.38	92.5
PSP	90.01	10,897	0.45	91.0
EWC	89.0	3,800	0.36	88.4
GEM (256)	88.5	12,300	0.60	85.5

In Table 7, BD+PSP, BD+EWC, PSP, EWC, and GEM (256) and their attributes in terms of performance metrics such as Accuracy, computational cost, energy consumption, and task retention are described. BD+PSP shows maximum Accuracy and retention of the tasks at 90.65% and 94.2%

respectively, thus crowned as the retention performance champion. EWC shows the least computational cost of 3,800 bytes and low energy efficiency at 0.36 joules, therefore being the most fitting in extremely resource-constrained environments. It significantly aids the assessment of every algorithm's efficiency against the cost of losses in Accuracy, aimed at the pragmatics of resource constrained environments.

5.2 Discussion

The outcomes delineated the progressions in accuracy for each variant, and the overall dominance for the strategies BD+PSP for knowledge retention over multiple tasks. Validation against the rest confirms the substantial progress achieved with the proposed algorithms, especially BD+EWC, BD+PSP, with regard to accuracy and computation time. The review also addresses the implications of these findings, underlining the effectiveness of bias-decoupled methods in continual learning, which broadens the applicability and resilience of artificial intelligence systems. The conclusions also illuminate the relative strengths and weaknesses of the various strategies which should inform further work in object recognition and continual learning.

6 Conclusion and Future Work

The systems designed by Colonel Adaptive AI IPN have multi-functionality and intellectual capability. Along exploring the biological, control and engineering aspects of machine learning, the holistic approach by IPN serves the fondest desires of a biologist towards AI. IPN proves practical machine learning, biology, control engineering, differential biologist and. The evidence supporting design and functional design merit of IPN or its variants, like BD-EWC and BD-PSP, have been applied to scenarios involving catastrophic 'forgetting' and object recognition to the CIFAR-100 dataset. The BD+PSP and its some variations are the most IPN designs that others have been benchmarked against in regard to efficacy. Moreover, the incorporation of IPN technology with mobile ad hoc networks and wireless sensor networks could improve real-time responsiveness and agility, thus becoming a component of next generation AI-enabled communication systems. There, however, is still plenty of room for improvement and exploration with IPN and its subclasses. Additional research may analyze network architecture optimization, substitutive regularization methods, and the broader applicability of IPN to large, heterogeneous data repositories. Further, research may be directed toward the inception of multiple new and novel applications of IPN in robotics, autonomous systems, healthcare, and cyber protection. Further studies should investigate what IPN can accomplish with privacy and data leakage problems in distributed computing settings. These concerns outline what IPN might solve regarding advancing AI and achieving truly adaptive and intelligent systems. Furthermore, IPN's proficiency with large and rapidly evolving datasets in well-lit settings might further enhance its utilitarian value.

Ethical Approval

This publication excludes any information about the authors' training with humanoids or animals.

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Conflicts of Interest

The authors have not revealed any relevant financial or non-financial interests in this paper.

Informed Consents

This page contains no studies the authors have done with humans or animals.

Authorship Contributions

Conceptualization: Vanaparthi Kiranmai, Dr. A. Manikandan; Methodology: Vanaparthi Kiranmai, Dr. A. Manikandan; Formal analysis and investigation: Vanaparthi Kiranmai, Dr. A. Manikandan; Writing - original draft preparation: Vanaparthi Kiranmai, Dr. A. Manikandan; Writing - review, and editing: Vanaparthi Kiranmai, Dr. A. Manikandan; Resources: Vanaparthi Kiranmai, Dr. A. Manikandan.

Data Availability

Any of the authors' experiments involving human or animal participants are not included in this article. We didn’t use any third-party data.

References

[1] Beltran-Carbajal, F., Yañez-Badillo, H., Tapia-Olvera, R., Rosas-Caro, J. C., Sotelo, C., & Sotelo, D. (2023). Neural network trajectory tracking control on electromagnetic suspension systems. *Mathematics*, *11*(10), 2272. https://doi.org/10.3390/math11102272

[2] Bergaoui, N., & Ghannouchi, S. A. (2023). A BPM-based approach for ensuring an agile and adaptive learning process. *Smart Learning Environments*, *10*(1), 40. https://doi.org/10.1186/s40561-023-00259-5

[3] Brücke, C., Härtling, P., Palacios, R. D. E., Patel, H., & Rabl, T. (2023). TPCx-AI-an industry standard benchmark for artificial intelligence and machine learning systems. *Proceedings of the VLDB Endowment*, *16*(12), 3649-3661. https://doi.org/10.14778/3611540.3611554

[4] Cromer, J. A., Roy, J. E., & Miller, E. K. (2010). Representation of multiple, independent categories in the primate prefrontal cortex. *Neuron*, *66*(5), 796-807. https://doi.org/10.1016/j.neuron.2010.05.005

[5] Cui, W., Xue, Z., & Thai, K. P. (2018, November). Performance comparison of an AI-based adaptive learning system in China. In *2018 Chinese automation congress (CAC)* (pp. 3170-3175). IEEE. https://doi.org/10.1109/CAC.2018.8623327

[6] Dasoulas, I., Yang, D., & Dimou, A. (2024, May). MLSea: a semantic layer for discoverable machine learning. In *European Semantic Web Conference* (pp. 178-198). Cham: Springer Nature Switzerland.

[7] Du, X., Venkataramanaiah, S. K., Li, Z., Suh, H. S., Yin, S., Krishnan, G., ... & Cao, Y. (2022). Efficient continual learning at the edge with progressive segmented training. *Neuromorphic Computing and Engineering*, *2*(4), 044006. https://doi.org/10.1088/2634-4386/ac9899

[8] Elkins, J. G., & Fahimi, F. (2024). Control-Theoretic Techniques for Online Adaptation of Deep Neural Networks in Dynamical Systems. https://doi.org/10.48550/arXiv.2402.00761

[9] Farivar, F., Jolfaei, A., Manthouri, M., & Haghighi, M. S. (2023). Application of fuzzy learning in IoT-enabled remote healthcare monitoring and control of anesthetic depth during surgery. *Information Sciences*, *626*, 262-274. https://doi.org/10.1016/j.ins.2022.12.094

[10] Grossberg, S. (2020). A path toward explainable AI and autonomous adaptive intelligence: Deep learning, adaptive resonance, and models of perception, emotion, and action. *Frontiers in neurorobotics*, *14*, 36. https://doi.org/10.3389/fnbot.2020.00036

[11] Hossain, N. U. I., & Shah, C. (2022). Dynamic bayesian network-based approach for modeling and assessing resilience of smart grid system. In *Handbook of smart energy systems* (pp. 1-20). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-97940-9_16

[12] Kabudi, T., Pappas, I., & Olsen, D. H. (2021). AI-enabled adaptive learning systems: A systematic mapping of the literature. *Computers and education: Artificial intelligence*, *2*, 100017. https://doi.org/10.1016/j.caeai.2021.100017

[13] Keuning, T., & Van Geel, M. (2021). Differentiated teaching with adaptive learning systems and teacher dashboards: the teacher still matters most. *IEEE transactions on learning technologies*, *14*(2), 201-210. https://doi.org/10.1109/TLT.2021.3072143
[14] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). Gradient-based learning applied to document recognition. *Communications of the ACM*, *60,* 84–90.
[15] Li, D., Han, H., & Qiao, J. (2021). Deterministic learning-based adaptive neural control for nonlinear full-state constrained systems. *IEEE Transactions on Neural Networks and Learning Systems*, *34*(8), 5002-5011. https://doi.org/10.1109/TNNLS.2021.3126320
[16] Li, F., He, Y., & Xue, Q. (2021). Progress, challenges and countermeasures of adaptive learning. *Educational Technology & Society*, *24*(3), 238-255.
[17] Li, S., Liu, H., Bian, Z., Fang, J., Huang, H., Liu, Y., ... & You, Y. (2023, August). Colossal-ai: A unified deep learning system for large-scale parallel training. In *Proceedings of the 52nd International Conference on Parallel Processing* (pp. 766-775). https://doi.org/10.1145/3605573.3605613
[18] Martin, F., Chen, Y., Moore, R. L., & Westine, C. D. (2020). Systematic review of adaptive learning research designs, context, strategies, and technologies from 2009 to 2018. *Educational Technology Research and Development*, *68*(4), 1903-1929.https://doi.org/10.1007/s11423-020-09793-2
[19] Merabet, A., Kanukollu, S., Al-Durra, A., & El-Saadany, E. F. (2023). Adaptive recurrent neural network for uncertainties estimation in feedback control system. *Journal of Automation and Intelligence*, *2*(3), 119-129. https://doi.org/10.1016/j.jai.2023.07.001
[20] Moskalenko, V., Kharchenko, V., Moskalenko, A., & Kuzikov, B. (2023). Resilience and resilient systems of artificial intelligence: taxonomy, models and methods. *Algorithms*, *16*(3), 165. https://doi.org/10.3390/a16030165
[21] Ouyang, F., Xu, W., & Cukurova, M. (2023). An artificial intelligence-driven learning analytics method to examine the collaborative problem-solving process from the complex adaptive systems perspective. *International Journal of Computer- Supported Collaborative Learning*, *18*(1), 39-66. https://doi.org/10.1007/s11412-023-09387-z
[22] Simpson, J., Oosthuizen, R., Sawah, S. E., & Abbass, H. (2021). Agile, antifragile, artificial-intelligence-enabled, command and control. https://doi.org/10.48550/arXiv.2109.06874
[23] Vitorino, J., Oliveira, N., & Praça, I. (2022). Adaptative perturbation patterns: Realistic adversarial learning for robust intrusion detection. *Future Internet*, *14*(4), 108. https://doi.org/10.3390/fi14040108
[24] Zhang, J., & Liu, Z. (2024). PerFreezeClip: Personalized federated learning based on adaptive clipping. *Electronics*, *13*(14), 2739. https://doi.org/10.3390/electronics13142739
[25] Zheng, S., Liu, W., Shen, S., Zang, Y., Wen, C., Cheng, M., & Wang, C. (2023). Adaptive local adversarial attacks on 3D point clouds. *Pattern Recognition*, *144*, 109825. https://doi.org/10.1016/j.patcog.2023.109825
[26] Zhong, X., & Ni, Z. (2023). A neural-reinforcement-learning-based guaranteed cost control for perturbed tracking systems. *IEEE Transactions on Artificial Intelligence*, *5*(6), 3205-3217, https://doi.org/10.1109/TAI.2023.3346334

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