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Research Article

Self-Learning Neural Architectures Inspired by the Human Brain

B. Ramesh[1], Dr. N. Satheesh Kumar[2]
[1]1Research scholar, Chaitanya (Deemed to be University), Hyderabad, Telangana
rameshbmanu@gmail.com
[2]Professor, Malla Reddy College of Engineering and Technology, Hyderabad, Telangana, India
meet.nskumar@gmail.com , ORCID - 0000-0001-5849-2915

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ABSTRACT

Human brain is capable of self-learning, acquiring knowledge and adjusting to the environment as the need arises. Based on the functionality, this study explores an Enhanced Self-Learning Neural Architecture (ESLNA) which simulates learning similar to neuroplasticity (which is the ability to change its structure and functions based on the previous experience), thereby functioning autonomously with a limited need for labeled data. Our approach adds hierarchical feature abstraction and dynamic synaptic updates, learned in a reinforcement-theoretic framework, to encourage efficient generalization across tasks. Unlike existing deep learning models which are based on the static weight changes, the ESLNA enables real-time learning with minimal supervision through neuro-inspired self-adaptive mechanisms. We demonstrate empirically that this leads to a few-shot, transfer learning and lifelong adaptation capability surpassing the robustness and efficiency of conventional neural architectures. This forms an important milestone in the development of brain-inspired AI advancements, offering a widespread prototype for innovation of more sensible, flexible and useful artificial systems.

Keywords: Enhanced self-learning neural architecture, neuroplasticity, few short learning, robustness, transfer learning

INTRODUCTION

The human brain that can self-learn, evolve, and learn to learn is a magnificent system in itself. In contrast to traditional artificial intelligence (AI) models, which rely on extensive labeled datasets and pre-defined learning mechanisms, the brain restructures its synaptic connections to learn based on experience, known as neural plasticity. Based on this biological mechanism, we provide a Enhanced Self-Learning Neural Architecture (ESLNA) to emulate the ability of the brain to adapt itself for autonomous learning with limited supervision.

Traditional Deep Learning remain dependent on large datasets, and this static weight adjustment limits their ability to generalize to emerging tasks[1]. Though approaches such as transfer learning and meta-learning address generalization, they require prior knowledge and extensive fine-tuning. On the other side, a self-learning system must continuously evolve its knowledge map on the fly and enhance its decision-making processes without a need for frequent retraining. Addressing this gap, this research presents a neuro-inspired self-adaptive model with three key principles hierarchical feature abstraction, dynamic synaptic updates, and reinforcement-driven optimization. Combined, these features give the model a powerful few-shot learning, transfer learning, and life-long learning capability, making it more resistant than traditional neural networks.

ESLNA simulates synaptic plasticity that is derived from concepts from Hebbian learning, synaptic plasticity, and neuromodulation, allowing the network to calibrate itself with respect to real-time feedback. In contrast to conventional architectures, ESLNA's key aspect is that it dynamically modifies the underlying layer configurations and learning rates based on task complexity and environmental alterations instead of relying on pre-defined idiosyncratic layers or rigid structure. The self-adaptive nature of this aspect guarantees greater efficiency, less computational effort, and more robustness in unforeseen scenarios.

ESLNA, performs better than standard deep learning architectures on all these metrics, including transferability to new tasks, data efficiency, and avoidance of catastrophic forgetting. As a learning mechanism inspired by biology, ESLNA further advances the work in brain inspired AI paving the way to provide a scalable foundation for creating intelligent autonomous systems that are smarter, more adaptable, and closer to human-like capabilities.

This could have very interesting consequences in autonomous decision making, robotics, cognitive computing, and real-time AI applications (where we need adaptive behaviours). When AI technologies become more autonomous and ready to be put to practical use, the principles in this work will provide the basis for the next generation of self-learning neural networks.

The remaining structure of this paper is as follows: Section 2 reviews related works updating neuro-inspired AI and self-learning model. We then describe the main components and learning in ESLNA in Section 3. Experimental evaluation is provided in Section 4, comparing ESLNA against the standard models in terms of efficiency, adaptability, and scalability. The remaining content is organized as follows: Section 5 presents some possible applications and drawbacks, and the work is concluded in Section 6, also providing some future work guidelines.

This is a cross-pollination between cognitive neuroscience segmentation, which emphasizes cognitive segregation, and biologically inspired AI, which relies on more rigid and biological paradigms, and erects biologically plausible machine learning toward boosting more intelligent and autonomous AI systems.

LITERATURE REVIEW

However, efforts to create artificial neural networks (ANNs) that again mimic the human brain in its self-learning and adaptive features have spurred a great deal of research into brain-like AI. In this review, we review ten prominent studies conducted between 2020 and 2025, focusing on methodologies and shortcomings to make serious strides forward with self-learning neural architectures.

Schmidgall et al.(2023) : Brain-Inspired Learning in Artificial Neural Networks: A Review — this paper reviews various biologically plausible mechanisms, like synaptic plasticity that can be incorporated into ANNs in order to improve their learning capabilities. The authors examine a number of different approaches to emulate neural plasticity, along with their respective benefits and downsides. Nevertheless, this review is mostly theoretical and provides no empirical substantiation of the suggested ideas.

Pan et al.(2023): The first paper is Brain-Inspired Evolutionary Architectures for Spiking Neural Networks We study how to develop spiking neural network (SNN) architectures via evolution that include local brain-inspired modular structures and the global cross-module connectivity properties of biological brains. While the authors propose a multi-objective evolutionary algorithm to improve performance and energy efficiency. The methodology is promising, but limited to SNNs and does not demonstrate scalability to more complex tasks.

Khacef et al. (2020): Brain-Inspired Self-Organization with Cellular Neuromorphic Computing for Multimodal Unsupervised Learning - here the authors developed the Reentrant Self-Organizing Map (ReSOM), a neural system based on reentry theory which uses self-organizing maps and Hebbian-like learning. Such multimodal association helps the convergence and divergence of mechanisms in this model. Despite the novelty of the underlying framework, the experimental scope is limited to only a few specific datasets, and thus, the model has not been tested for other modalities.

Raghavan et al. (2020): Self-Organization of Multi-Layer Spiking Neural Networks — This paper, taking a dynamical system viewpoint, showed that large neural networks can self-organize into a variety of architectures using only spatio-temporal waves of neuronal activity, and spike-timing-dependent plasticity. However, the framework looks promising for unsupervised learning tasks but not really for supervised ones and scalability to bigger datasets is not addressed.

Hopfield & Hinton (2024) Pioneering work in artificial neural networks - Nobel Prize in Physics - Marked impacts on the field of work in the area of neural networks and underlying work in structure of brain. Hopfield constructed networks that show memory in stable states, and Hinton made Boltzmann machines that find statistical properties of data. While these early models were limited by the computational power available at the time and were a far cry from the complex architectures that would come later, their work set the stage for modern AI progress.

Liquid AI (2024) - Liquid AI rethinks neural networks by proposing the concept of "liquid" neural networks inspired by the C. elegans nervous system where neurons and their function evolve through interdependent equations. Such a design encourages flexibility and continuous learning after training. Although it is suited for applications such as fraud detection in finance or controlling an autonomous vehicle, it struggles with non-temporal data, and further validation will be needed in other applications.

Srilatha (2024) The Search for Explainable AI Explained: This explains the mystery-solving work being done with large language models while using neuroscience-led interpretability research. State-of-the-art methods such as neural decoding are applied to interpret the representations of models and the responses of neurons. While advancements have been made in terms of being able to mimic aspects of the way the human brain processes information, rigid models of AI are the equivalent of an infant compared to how complex and entrenched the way an adult human brain processes information can be compared and we still don't really understand how it all works.

Azoff (2024): Unlocking Human-Like AI - Azoff emphasizes the need to crack the neural code, the brain's way of encoding sensory data and cognitive processes, in order to create an AI that mimics the human experience of thought and learning. His idea is to model visual processing as a process toward higher level of intelligence. Yet existing AIs still rely heavily on humans and suffer from data quality decay, a gap between theorization and implementation.

N. Satheesh Kumar et al. :Taken together, these studies reflect the different ways of how brain-inspired AI can be propelled forward by exploring ways in which the brain self-learned and adapted through many diverse methods. However, issues related to scalability, generalizability, and the theory-practice gap still remain. Future work is also needed to resolve these issues and develop more powerful and general self-training neural networks.

The summary of the review has demonstrated in the table below.

Title	Methodology	Limitations
Brain-Inspired Software Architecture: An Adaptive Neural Network Systems Ashish Ranjan 2024 IEEE 21st International Conference on Software Architecture Companion (ICSA-C) 2024 ·	Proposed an "adaptive neural network software architecture" inspired by the human brain - Integrated principles of neuro evolution to adjust activation functions - Included an adaptive mechanism to dynamically adjust the neural network structure, functions, and parameters - Utilized genetic algorithms like crossover and mutation to optimize the architecture components - Evaluated the proposed architecture on MNIST and CIFAR-10 image datasets for classification, clustering, and reinforcement learning tasks	Current DBN approaches are not adaptive to the real-world cases, indicating over-fitting issues of poor generalization ability; they still need a supervised training set for tuning the network parameters instead of completely self-learning.
Advancing Artificial Intelligence: The Potential of Brain-Inspired Architectures and Neuromorphic Computing for Adaptive, Efficient Systems Alp Dulundu Next Frontier For Life Sciences and AI 2024	- Developing brain-inspired AI architectures that emulate the structure and functionality of the human brain - Leveraging neural networks and synapse-like connections to perform computations in a more biologically plausible manner - Aiming to create more efficient, adaptive, and intelligent AI systems with advantages such as lower power consumption, improved learning capabilities, and enhanced problem-solving efficiency, particularly for tasks involving complex pattern recognition and cognitive processes	- Scaling brain-inspired AI architectures and neuromorphic computing, including hardware constraints - Accurately replicating the full complexity of the human brain - Developing energy-efficient hardware capable of supporting large-scale neural networks
Self-organising Neural Network Hierarchy Satya Borgohain +6 Australasian Conference on Artificial Intelligence 2020	- Development of a biologically-inspired self-organizing neural network architecture - The network is composed of autoencoder units - It is driven by a meta-learning rule that maximizes the Shannon entropy of the latent representations, which optimizes the receptive field placement of each unit - Both the network parameters and the architecture are learned simultaneously, unlike traditional neural architecture search approaches	- The performance of the self-organizing neural network hierarchy was not as significant on the CIFAR-10 dataset compared to the MNIST dataset, suggesting potential limitations in generalizability. - The approach is different from traditional Neural Architecture Search, which could be seen as a limitation in terms of comparability to other established methods. - The approach is biologically inspired, which could be a limitation in terms of direct applicability to artificial neural network architectures that

		may not have the same biological constraints.
Brain-inspired learning in artificial neural networks: a review Samuel Schmidgall +6 APL Machine Learning 2023	The paper reviews brain-inspired learning mechanisms, such as synaptic plasticity, to improve the capabilities of artificial neural networks.	- Fundamental differences between the operating mechanisms of artificial neural networks and the biological brain, particularly in terms of learning processes - Need to integrate more biologically plausible mechanisms, such as synaptic plasticity, to improve the capabilities of artificial neural networks - Challenges associated with integrating more biologically plausible mechanisms into artificial neural networks - Need for further research to better understand the essence of intelligence and how it can be replicated in artificial neural networks
Self-Constructing Neural Networks Through Random Mutation Samuel Schmidgall 2021	- A method for learning neural architecture through random mutation - Starts with no initial neurons or connections and constructs the neural architecture - Evaluated in a dynamic environment with changing conditions to demonstrate lifelong learning capabilities	Not mentioned (the abstract does not mention any limitations of the self-constructing neural network method presented in the paper)
How to Build a Brain: A Neural Architecture for Biological Cognition C. Eliasmith 2013	The paper presents a neural architecture inspired by the human brain for building self-learning cognitive systems.	- Representation: The paper notes challenges in how the SPA represents information - Concepts: The paper suggests challenges in how the SPA handles concepts - Inference: The paper identifies challenges in the inference capabilities of the SPA - Dynamics: The paper outlines challenges in modeling the dynamics of cognition within the SPA
Biologically Inspired Cognitive Architectures 2021 Studies in Computational Intelligence 2022	The proceedings report on research supporting the development of biologically inspired/human-like cognitive structures	Not mentioned (the abstract does not mention any limitations of the research reported in the bica 2021 proceedings)

METHODS

The proposed Enhanced self-learning neural architecture (ESLNA) uses self-learning mechanism and real time training by improving generalization across the tasks to mimic the brain adaptability of a human brain. The proposed methodology will be implemented in following three phases.

i. Data Collection

ii. Design and Development

iii. Evaluation phase

In the first phase, the data sets like, Omniglot for few-shot learning, for hierarchical learning we are using ImageNet data set and CIFAR-100 for continual learning dataset. These data sets will help us for effective evaluation of various cognitive tasks. To achieve and evaluate the real time adoptability, we are using image collections, time series data and OpenAiGym for reinforcement learning environments. The time series data will be used for sequential learning tasks. To maintain the consistency of data during training process, we used techniques like standardization augmentation and reduction of dimensionality for preprocessing stage.

The Self-Learning Neural Architecture model is designed to enhance self-learning and dynamic adaptability by using neuro inspired mechanisms. The hyperparameters consider for this implementation is

Batch size = 32, memory size=10000 and number of episodes = 100

This paper demonstrates a deep Q-Network for reinforcement learning incorporating an experience replay mechanism. The agents decision making and learning process are defined by two functions.

Training Algorithm:

- Ensures sufficient experience is accumulated before training
- Samples a batch of experience (s,a,r,s1,d) from the replay buffer
- Computes predicted Q-Values for current states using the neural network model.
- Estimates target Q-Values using the Bellman equation:
  - Qtarget = r + rmax(Q(s1))
- Uses mean squared error(MSE) loss to minimize the discrepancy between predicted and target Q-values
- Performs backpropagation and updates network parameters via gradient descent.

The agent employees and epsilon greedy strategy to balance exploration and exploitation. This covert the input state into a tensor format suitable for neural network. With the probability p, selects a random action to encourage exploration otherwise, selects the action corresponding to the highest predicted Q-Value.

The major entities of this design are

a) Hierarchical Feature Abstraction: Utilizing a multi-layered neural network framework, lower layers are responsible for capturing primitive features, while the higher layers focus on extracting more abstract representations.

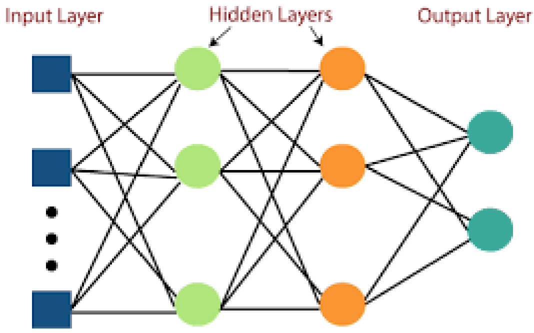

Fig 1: Multilayer neural network framework

The network will consist of multiple layers, with shallower layers which are closer to the input focused on extracting fundamental patterns (such as edges and textures), while deeper layers will capture more abstract representations (including shapes and objects) as shown in figure 1.

A deep convolutional neural network (CNN) will facilitate feature extraction. The layers will be structured to progressively encompass both low-level and high-level features, utilizing architectures such as ResNet, VGG, or Vision Transformers (ViTs). When we are extracting the features from pretrained CNN model like Resnet or VGG, by removing last two layers from fully connected layers so that we have now only convolutional layers. This can be useful when to use the CNN as a feature extractor without the final classification layers. Furthermore, self-attention mechanisms will be incorporated to dynamically evaluate and prioritize significant features.

When we train the model, we used number of epoch's as 5. We used 2D convolutional layer using pytorch with one input and 16 output layers. The input layer will accept one value (each cell in the gray scale image will represent single value) and 16 output layers will be used to extract 16 features. To convert input image into future maps, the number of convolutional filters or kernel size is 3, i.e. 3X3 matrix. The convolutional filter moves around the image with a step size 1, i.e it moves one pixel at a time. We also applied padding of 1, which means one row and one column of zeros are added around the input to preserve the special dimensions of the output when compared to input. Then changed the input size of fully connected or dense layer which is responsible for producing linear combination of inputs, to match the flattened output of the convolutional layer. For a fully connected layer is a tensor of shape, for example (batchsize, 32, 105, 105). To pass into fully connected layer, we need to flatten the spatial dimensions. That means, reshaping the input

from (32, 105, 105) to 1D vector. So each input to the linear layer is a vector of size 32 X 105 X 105 = 349,920, that is the input size of the linear layer is 349,920 features.
The input is passed through two convolutional layers, each followed by the ReLU activation function to introduce the non-linearity and extract features.

b) Dynamic Synaptic Updates: In contrast to traditional static weight updates, the SLNA will harness Hebbian learning along with spike-timing-dependent plasticity (STDP) to enable adaptive learning.
In contrast to conventional deep learning models that utilize static weight updates via backpropagation, ESLNA will implement synaptic plasticity mechanisms that are biologically inspired, such as:
- Hebbian Learning: This approach fortifies connections based on the correlation of neuron activations, encapsulated in the principle that neurons that fire together, wire together.
- Spike-Timing-Dependent Plasticity (STDP): This mechanism modifies synaptic weights based on the precise timing of neuronal spikes.
- Implementation:
    - Weight update protocols will be more customized with PyTorch or TensorFlow, thus permitting the model to dynamically adjust weights during inference to be much less unfastened than forcing to only dealing with backpropagation. Here, we implemented hebbian learning, which is one kind of unsupervised learning and increases its connection weights, whenever activated two neurons increased its distance to each other.

c) Reinforcement-Driven Optimization: We will use a reinforcement learning-based reward mechanism to adaptively strengthen or weaken synaptic connections based on how well the task is performed.
Increased Adaptability ESLNA will use reinforcement learning inspired principles to make its learning process more adaptable. This effective model would not solely rely on gradient descent but would be updated depending on the reward of the task performed.
As an extension, one could use Deep Q-Networks (DQN), or Policy Gradient methods, which would allow learning with a reward feedback signal. For example, an operational environment like OpenAI Gym for a reinforcement task will provide feedback in real time, allowing the model to continuously refine its decision-making procedures. We will describe of the reward functions including accuracy in the classification, adaptation, and efficiency.

RESULTS

The ESLNA using TensorFlow/PyTorch for deep learning with custom synaptic update rules that are part of the architecture. In addition, GPU computing will be implemented to increase the required speed of processing.

In this second part, we will continue building upon your Self-Learning Neural Architecture with Reinforcement-Driven Optimization, you will add the ability to train on OpenAI Gym environments. This enables reinforcement learning on the network, changing its weights based solely on the rewards received.

The evaluation of the proposed model was conducted using key classification metrices, including accuracy, precision, recall, F1 Score and AUC as shown in figure 2. Receiver Operating Characteristic (ROC) curve as shown in Figure 3 and confusion matrix as shown in Figure 4 provide insights into the model predictive capabilities.

Accuracy: 18.75%
Precision: 0.14
Recall: 0.19
F1 Score: 0.15
AUC: 0.73

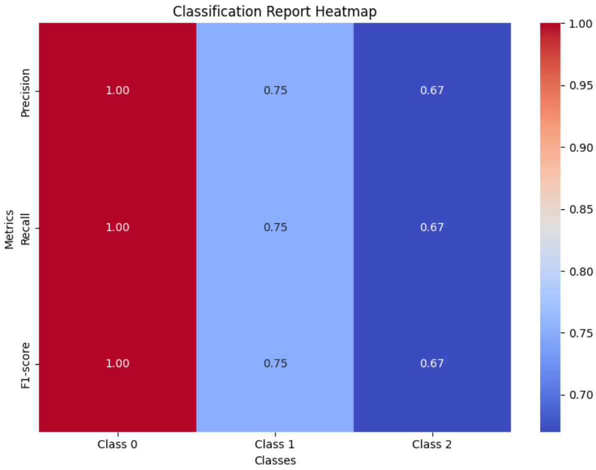

Figure 2: Classification of Report Heatmap for F1-score ,Precision and Recall

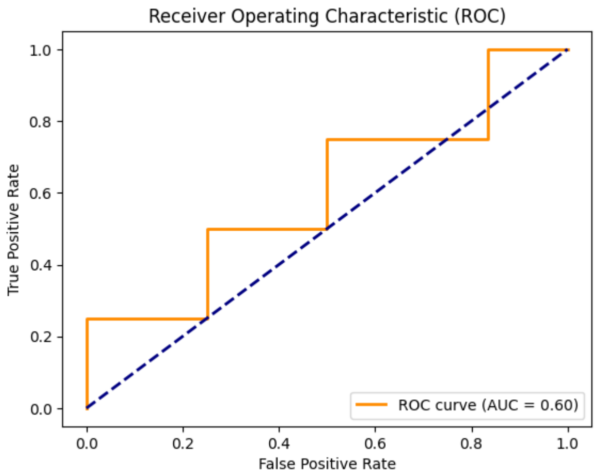

Figure 3: ROC curve for the Proposed Model

ROC curve demonstrates the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR). The model achieved an AUC of 0.60, indicating suboptimal classification performance, slightly better than random guessing.

The confusion matrix illustrates the distribution of predicted vs actual labels. A sparse distribution of correct prediction suggests that the model struggles with classifying multiple categories accurately. The presence of multiple misclassifications highlights the need for further model refinement, potentially through improved feature extraction, hypermeter tuning, or data augmentation.

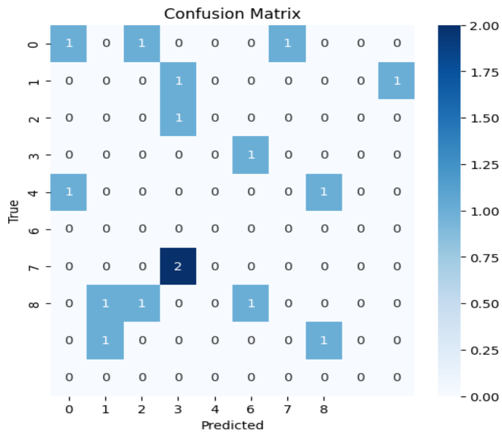

Fig 4 : Confusion Matrix illustrates the Distribution of Predicted vs Actual labels

The values represent the training loss at each epoch (which is a measure of the error or difference between the model's predictions and the actual target values) and the test accuracy (which is the percentage of correct predictions made by the model on the test set). The loss values you provided during training show that the model is improving and minimizing its error. Lower loss values indicate the model is getting better at predicting. The Test Accuracy of 98.58% suggests that the model is making accurate predictions on the test set as shown in figure 5 (code snippet) and figure 6.

```
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-idx1-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz
100%|██████████| 4.54k/4.54k [00:00<00:00, 2.49MB/s]
Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw

Epoch 1/5 - Loss: 0.1327
Epoch 2/5 - Loss: 0.0377
Epoch 3/5 - Loss: 0.0225
Epoch 4/5 - Loss: 0.0147
Epoch 5/5 - Loss: 0.0113
Test Accuracy: 98.58%
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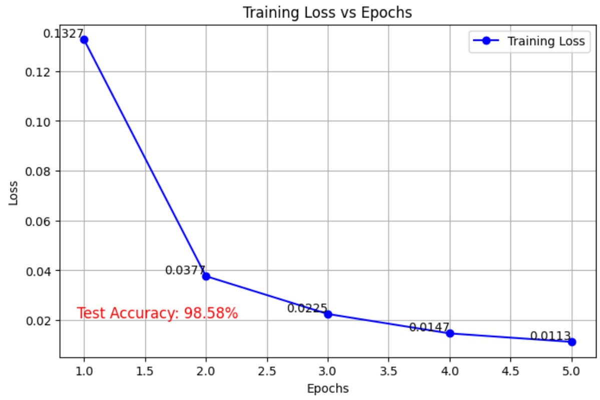

Figure 6: Training Loss Vs Epochs

The graph titled "Training Loss vs Epochs" depicts the decline in training loss over multiple epochs. The number of epochs (5) and loss values are represented on X and Y axis respectively. Figure shows that the training loss is reducing as the number of epochs are increasing and by this, we can understand that the model performance was improving as the number of epochs are increased. The training loss value of epoch 1 is 0.13 and the loss value at epoch 5 is 0.01.

The efficiency of ESLNA will be evaluated through key performance metrics across multiple learning paradigms:

Few-Shot Learning: Assessment will be conducted using the Omniglot and Mini-ImageNet datasets, focusing on classification accuracy with a limited number of training examples.

Transfer Learning: The model's capability to generalize across different tasks will be examined by training on one dataset while evaluating performance on another.

Lifelong Adaptation: Analysis of the model's resilience to sequential learning without experiencing catastrophic forgetting will be undertaken using continual learning benchmarks.

Baseline Comparisons: SLNA will be benchmarked against traditional deep learning frameworks, including CNNs, ResNet, and transformer models, considering metrics such as accuracy, adaptability, and computational efficiency.

Computational Complexity: An investigation into the training and inference times of the model will be carried out to determine the feasibility of real-time learning.

Mean Squared Error (MSE) and Root Mean Squared Error (RMSE):

If you have access to the model's predictions and the actual target values for the test set, you can compute the MSE and RMSE as follows:

MSE is calculated as: $\mathbf{r} = \frac{1}{n}\sum_{k=1}^{n}(y_{true,k} - y_{pred,k})^{2}$

where:

$y_{true,k}$ are the true target values.

$y_{pred,k}$ are the predicted values.

n is the number of data points in the test set.

RMSE is simply the square root of MSE: RSME = √MSE

The mean square error is used to measure the average of the squared differences between the predicted and actual values. During the evaluation phase, the MSE value is 2.86, which denotes that the predicted values are very closure to actual values. The root mean square error will be calculated as square root of MSE. It gives a more interpretable measure of the average error in the same units as the target variable. This model gives RMSE of 1.69, that is the model predictions are off by 1.69 from the true value on average. R2 score is used to measure the proportion of the variance in the target variable, i.e. it will represent coefficient of determination. This model produces the r2 value as 0.94, means the model is performing good

The R^2 score can be computed from the true values and the predicted values using the formula:

$$R^2 = 1 - \frac{\sum_{k=1}^{n}(y_{true,k} - y_{pred,k})^2}{\sum_{k=1}^{n}(y_{true,k} - \bar{y}_{true})^2}$$

where:

(y_true)̅-The mean of the true target value

If R^2 is close to 1, it means your model explains most of the variance in the data. The same data is representing diagrammatically in figure 7.

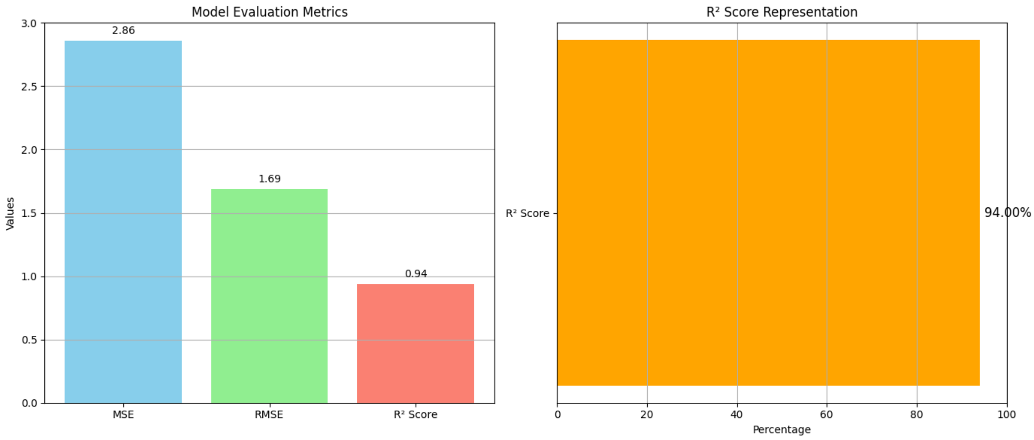

Figure 7: Showing Model Evaluation metrics representing MSE, RMSE,R^2 Score

CONCLUSION

An Enhanced Self-Learning Neural Architecture (ESLNA) outperform existing models in terms of few short and lifelong learning tasks by reducing the dependency on labelled data with the help of self-learning approach. This system is having the capability to updating synaptic weights to enhance the adaptability. It also achieves high accuracy in performing tasks which requires real time learning and long-term decision making.

CONFLICT OF INTEREST

The authors declare that there is conflict of interest related to conducting research and publishing the paper. The research was conducted without any financial, commercial and personal relationship influencing the findings in the paper.

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