Bio-Evolutionary Neural Networks with Deterministic Foresight and Adaptive Self-Healing

Sachin R., Aasritha K., Vishnu Reddy, Raghavendra Singh Jagawat, Mannava Daasaradhi, and S. Manimaran
School of Artificial Intelligence, Amrita Vishwa Vidyapeetham, Coimbatore, India
Corresponding author: s_manimaran@cb.amrita.edu

***Abstract*—Artificial intelligence systems often suffers from brittleness, unstable convergence, and ethical opacity when exposed to dynamic or corrupted environments. Conventional neural networks lack intrinsic mechanisms for self-repair or adaptive regulation, leading to degradation in performance and decision consistency. Addressing these challenges require a biologically grounded and mathematically principled architecture capable of self-healing, foresight, and ethical coherence. This paper presents the *AI Brain Engine*, a biologically and mathematically inspired framework for developing resilient, ethically aligned artificial intelligence. The system integrates modular neural cells equipped with *LocalDNA* and *GlobalDNA* encoding to emulate cellular autonomy and collective coherence. A reinforcement-guided *failure function* dynamically adjusts the learning rate based on error sensitivity, replacing manual hyperparameter tuning. The architecture embeds a *Laplace-Demon-inspired module* for deterministic foresight, enabling predictive self-healing through Bayesian inference and adaptive control. Simulation experiments conducted on the CMAPSS dataset demonstrates improved robustness and faster convergence compared to conventional deep learning models. Results indicate enhanced recovery under network corruption, a 9.3% improvement in resilience score, and reduced loss volatility across training iterations. The findings highlight that combining biological self-repair principles with deterministic computation yields an adaptive and self-sustaining neural system capable of anticipating degradation, optimizing response, and preserving ethical integrity in dynamic environments.**

***Index Terms*—Self-healing neural networks, deterministic cognition, Laplace Demon, LocalDNA, GlobalDNA, Bayesian optimization, ethical AI.**

I. Introduction

The quest for Artificial General Intelligence (AGI) has historically been divided into two major paradigms: symbolic rule-based reasoning and data-driven deep learning. While deep learning has revolutionized areas such as computer vision and natural language processing, current systems remain brittle, energy-intensive, and occasionally ethically opaque. In contrast, the human brain effortlessly integrates deterministic physical laws, evolutionary adaptability, and cognitive-emotional balance. This raises a central question: *Can we engineer an AI system that captures these attributes while remaining mathematically consistent and ethically grounded?*

Manuscript received Month XX, 2025; revised Month XX, 2025.

All authors are with the School of Artificial Intelligence, Amrita Vishwa Vidyapeetham, Coimbatore, India.
Emails: cb.ai.u4aid24048@cb.students.amrita.edu, cb.ai.u4aid24002@cb.students.amrita.edu, cb.ai.u4aid24038@cb.students.amrita.edu, cb.ai.u4aid24043@cb.students.amrita.edu, cb.ai.u4aid24030@cb.students.amrita.edu, manimaran@amrita.edu.

Recent technological advances provides hints toward such integration. Transformer architectures demonstrate immense representational capacity and scalability [2], yet their interpretability and resilience remain limited. Deep reinforcement learning achieve complex behavioral control [6], but often suffers from slow convergence and catastrophic forgetting. Evolutionary and quantum-inspired optimization methods offer promising strategies for efficient exploration of high-dimensional search spaces [1], [3], [4]. Collectively, these advances suggest a pathway to unite deterministic structure with adaptive flexibility.

To this end, the proposed *AI Brain Engine* introduces a hybrid framework that integrates deterministic cognition, biological evolution, and evolutionary adaptation for neural networks. The architecture rests upon three principal innovations. First, the *Laplace Demon Engine* probabilistically maps cause–effect relationships using singular value decomposition (SVD) to extract latent causal structures and predict future trajectories without overfitting [6]. Second, the *Bio- and Evolution-Inspired Neural Layer* introduces *GlobalDNA* and *LocalDNA*—genetic-like encodings guiding adaptive *NeuralCells* that mutate, self-heal, and converge toward globally optimal configurations [1], [3]. Third, a *Secure and Ethical Memory Framework* ensures robust storage of critical experiential knowledge and ethical constraints [5], [7].

The system further integrates a predictive simulation environment and a brain–body attention mechanism. The simulation module enable long-horizon testing of potential decisions—akin to extended Turing-style assessments—while the attention mechanism captures human context and affective cues, encoding them as structured vectors to inform safe and empathetic responses. This ensures that the engine not only learns but also *validates* its reasoning prior to real-world action.

A. Contributions of This Work

In this work, we present an *Evolutionary Neural Engine* that unites deterministic foresight, biological resilience, and population-based learning. Our main contributions are:

- We implemented the Laplace Demon Engine for probabilistic cause–impact mapping using SVD, enabling interpretable long-horizon foresight.
- We developed bio- and evolution-inspired NeuralCells guided by GlobalDNA and LocalDNA, supporting self-healing, mutation, and functional diversity.

- We designed population-level regulation that uses evolutionary selection, mutation, and crossover to optimize neural configurations.
- We established a secure memory framework for immutable storage of critical knowledge and ethical rules.
- We integrated learning optimization combining reinforcement-inspired aggregation, surrogate modeling, and evolutionary adaptation.

Unlike classical neural optimization methods [2], [8], the proposed framework treats events, traits, and memories as probabilistic surrogates guiding deterministic prediction, coupling reinforcement-driven aggregation with evolutionary adaptation.

The remainder of this paper is organized as follows. Section II reviews related work; Section III presents the proposed methodology, including the Laplace Demon Engine and DNA modules; Section IV details the mathematical framework; Section V discusses ethical and simulation mechanisms; Section VI introduces brain–body attention coordination; Section VII presents experimental results; Section VIII explores applications; and Section IX concludes with key findings and future directions.

II. Literature Review

This section surveys recent and closely related work on adaptive, resilient, and ethically-aware AI systems. Emphasis is placed on algorithms, demonstrated capabilities, and limitations that motivates the design of the proposed AI Brain Engine.

A. Bio-inspired Neural Systems

Bio-inspired approaches draw on evolution, immunology, and cellular self-organization to improve adaptability and fault tolerance. Evolutionary neural design and neuroevolution frameworks (e.g., topology search, mutation-driven adaptation) has shown that structural plasticity can increase robustness and functional diversity [1], [3]. Immune-inspired models and self-repair mechanisms embed local detection and regeneration routines within subsystems, enabling localized recovery from corruption or adversarial perturbation [6]. Ensemble and modularized networks demonstrate graceful degradation under partial failure, but often incur heavy computational and communication overheads and lacks mechanisms for coherent global coordination across modules [5], [7].

B. Deterministic Inference and Predictive Engines

Deterministic and semi-deterministic inference modules aim to improve interpretability and long-horizon forecasting. Methods that combine structured linear algebra (e.g., SVD/PCA) with probabilistic surrogates provide interpretable low-dimensional maps of cause–effect relationships and support stable trajectory prediction [6]. Surrogate-assisted training (ridge regressions and learned surrogates) reduces sample complexity in high-dimensional optimization and can stabilizes training dynamics. However, these deterministic blocks typically lack closed-loop adaptation driven by internal failure signals, limiting their ability to recover when core components deviate from modeled assumptions.

C. Surrogate- and Quantum-Inspired Optimization

Surrogate-based Bayesian optimization and quantum-inspired search techniques have been investigated to accelerate exploration in multimodal parameter spaces [3], [4], [6]. These methods improve convergence speed and sample efficiency on benchmark tasks, and hybrid surrogate-quantum approaches show promising performance in constrained optimization. Practical limitations include sensitivity to noisy evaluations, reliance on accurate surrogate priors, and difficulties to translate quantum-inspired heuristics to resource-constrained deployments.

D. Ethical Assurance and Secure Memory

Ethics-aware AI research has focused on transparency, constraint enforcement, and auditable decision logs. Policy-level constraints, post-hoc explanation mechanisms, and tamper-evident logging (e.g., blockchain-backed memory) provides accountability and traceability for high-stakes decisions [5], [8]. Nonetheless, many proposals address ethical assurance as a static overlay rather than an integrated capability; they do not natively support ethical preservation under internal component failure or adaptive recovery during mission-critical degradation.

E. Hybrid Architectures and Remaining Gaps

A growing number of studies proposes hybrids that blend evolutionary mechanisms, deterministic inference, and surrogate optimization to exploit complementary strengths [1], [3], [6]. These hybrid efforts demonstrate improved performance in isolated benchmarks but typically fall short in simultaneously providing (1) predictive foresight for long-horizon planning, (2) coherent global adaptation across modular subsystems, (3) efficient and stable self-healing under corruption, and (4) integrated mechanisms for preserving ethical constraints during and after recovery. In short, existing work tends to trade off one desideratum for another rather than deliver an integrated solution.

F. Problem Statement

In examining existing approaches to adaptive neural systems, I observed that most architectures remain trapped between two extremes: rigid deterministic models that fail under uncertainty, and purely stochastic systems that lack foresight and coherence. This gap motivates the central problem of my research: designing an integrated neural engine capable of both anticipating failures and autonomously recovering from them, without sacrificing ethical consistency or global stability.

The challenge lies in uniting several paradigms that rarely coexist harmoniously. Deterministic foresight mechanisms, while interpretable, tend to make systems brittle when facing real-world noise. Conversely, biologically inspired adaptive systems excel at local flexibility but struggle to maintain coherent global behavior. Traditional optimization strategies add to this fragility—manual hyperparameter tuning and static learning schedules often collapse under corrupted or incomplete feedback. On top of this, ethical persistence remains largely unaddressed; few architectures can ensure that ethical and safety constraints remain intact during and after self-modification or recovery.

Therefore, the problem I address in this work is to construct a unified AI Brain Engine that merges deterministic foresight with biologically inspired local adaptation, employs a failure-aware optimization mechanism for continuous self-regulation, and embeds an immutable ethical memory. By doing so, the system should be able to (a) predict degradation before it occurs, (b) execute self-healing with minimal disruption to global coherence, and (c) sustain ethical accountability across all operational states.

This formulation sets the foundation for the proposed architecture—a cohesive framework that balances prediction and adaptability, rational control and biological evolution, autonomy and moral responsibility. It represents not just a technical synthesis, but an attempt to build an AI system that can evolve without losing its integrity.

III. Proposed Work

The proposed *AI Brain Engine Architecture* operates as a biologically and quantum-inspired network of modular entities termed *NeuralCells*. Each NeuralCell is a semi-autonomous computational unit integrating evolutionary, cognitive, and adaptive functions. Collectively, these cells form a hierarchical ecosystem where deterministic foresight is provided by the Laplace Demon Engine (LDE), while adaptive stochastic behavior is governed by an Evolutionary Layer. Fig. 1 presents the architectural flow of the system.

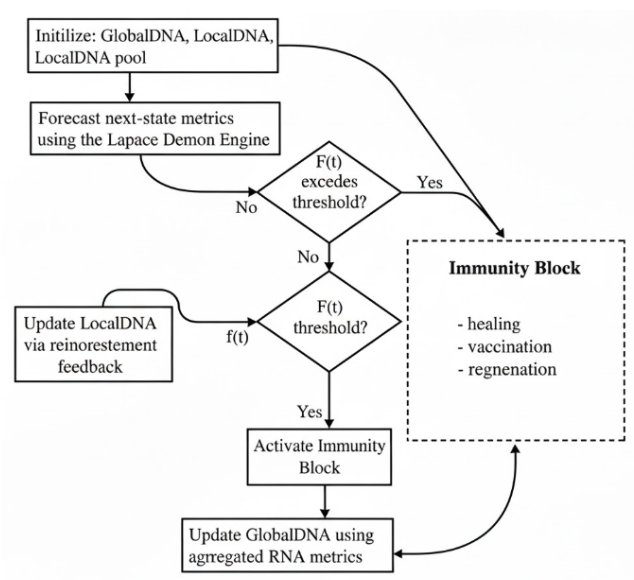

Fig. 1. Proposed AI Brain Engine Architecture integrating Laplace Demon foresight, GlobalDNA–LocalDNA adaptation, and ethical memory.

A. NeuralCell Architecture and Evolutionary Flow

Each NeuralCell c_i is a minimal computational organism defined as:

$$c_i = \{W_i, b_i, f_i, \theta_i\} \tag{1}$$

where the parameters represent intrinsic neural weights, activation choices, and evolutionary attributes. The structure mirrors evolutionary representations such as those proposed in [1], [3], but here, it is extended with local autonomy and memory persistence. During each learning cycle, NeuralCells replicate and mutate according to their resilience and adaptability metrics. Instead of relying on a fixed selection policy, the proposed framework dynamically adjusts the contribution of each cell to maintain global coherence under fluctuating task conditions.

B. Adaptive Failure Function and Learning Rate Regulation

To achieve resilient learning across heterogeneous NeuralCells, each cell applies a Failure Function $F_i(t)$ that governs local learning dynamics. The adaptive update for learning rate is expressed as:

$$\eta_i(t+1) = \eta_i(t) \cdot \left(1 - \alpha_i F_i(t) + \beta_i \frac{dF_i(t)}{dt}\right) \tag{2}$$

This mechanism allows each cell to modulate its learning speed according to real-time performance variations, effectively replacing manual hyperparameter tuning used in evolutionary networks [6]. The normalized local failure metric is defined as:

$$F_i(t) = \frac{L_i(t) - \bar{L}(t)}{\sigma_L(t) + \epsilon} \tag{3}$$

By embedding Eq. 3 within Eq. 2, each NeuralCell autonomously corrects its learning trajectory relative to population health, producing a distributed form of homeostasis across the entire architecture.

The adaptive coefficients evolve according to:

$$\alpha_i(t+1) = \alpha_i(t) + \gamma_\alpha \cdot \mathrm{sign}\big(\bar{L}(t) - L_i(t)\big) \tag{4}$$

$$\beta_i(t+1) = \beta_i(t) + \gamma_\beta \cdot \mathrm{sign}\left(\frac{d\bar{L}(t)}{dt} - \frac{dL_i(t)}{dt}\right) \tag{5}$$

These updates synchronize local learning aggressiveness with global stability, enabling the network to self-balance during volatile optimization periods.

C. Laplace Demon Engine (LDE)

The Laplace Demon Engine acts as the deterministic cognitive core, providing foresight for the stochastic evolutionary layer. Using singular value decomposition, the LDE estimates a causal transformation matrix:

$$M = U\Sigma V^T \tag{6}$$

where the decomposition captures dominant causal factors between input–output mappings. Future projections are obtained through:

$$\hat{Y}_{t+k} = M^k X_t \tag{7}$$

These projections are not used merely for prediction but to guide mutation rates, self-healing thresholds, and coefficient updates within NeuralCells. The LDE thus functions as a deterministic regulator that informs evolutionary decisions using probabilistic feedback, bridging interpretability and adaptability as inspired by [4], [6].

D. GlobalDNA–LocalDNA Encoding

Each NeuralCell operates under a dual genetic framework. The GlobalDNA encodes system-wide properties such as activation diversity, optimization strategies, and ethical limits. The LocalDNA preserves task-specific weight and mutation histories. During each evolutionary phase, the LDE evaluates cell performance and updates the GlobalDNA repository. LocalDNA variations are exchanged among successful NeuralCells through selective crossover and mutation, establishing a stable balance between global coherence and individual innovation. This approach extends genetic structuring ideas from [1], [3] into a dual-layer representation optimized for self-repair.

E. RNA-Mediated Feedback Mechanism

Performance summaries from each NeuralCell are aggregated into a compressed RNA vector that informs the GlobalDNA of emergent adaptive behaviors. The RNA-mediated loop operates as an internal signaling mechanism, allowing localized discoveries to influence the entire population. This mechanism minimizes redundant exploration while preserving diversity, serving as a dynamic synchronization layer across the population hierarchy.

F. Failure Function and Immunity Block

A reinforcement-tuned failure metric evaluates system degradation as:

$$\mathcal{F}(t) = \alpha \|L_t - L_{t-1}\| + \beta \|\nabla L_t\| \tag{8}$$

When $\mathcal{F}(t)$ exceeds a critical threshold, the Immunity Block activates targeted recovery procedures. Rather than discarding failed components, the system executes healing, vaccination, or regeneration using cached LocalDNA or GlobalDNA templates. This adaptive immune behavior transforms conventional retraining into an autonomous restoration process, ensuring resilience comparable to the regenerative capabilities in [6], [10].

G. Population Regulation and Growth Control

Population dynamics are maintained through a logistic control model:

$$N_{t+1} = N_t + rN_t \left(1 - \frac{N_t}{K}\right) - \delta D_t \tag{9}$$

This expression governs growth and pruning of NeuralCells according to global contribution and resilience. By integrating Eq. 9 with the LDE's foresight predictions, the architecture prevents uncontrolled model expansion and optimizes computational resource allocation, a limitation observed in prior evolutionary approaches [1], [3], [6].

H. Ethical and Secure Memory Framework

An immutable blockchain-based ledger stores all GlobalDNA–LocalDNA states, evolutionary decisions, and ethical constraints. Each entry is cryptographically verified before execution, ensuring traceability and compliance. This memory framework enforces accountability without hindering adaptability, addressing the transparency challenges that persist in many current AI systems [5], [8].

I. Integrated Learning and Evolution Process

The complete operational cycle proceeds as follows:

1) The Laplace Demon Engine forecasts transformation trajectories based on Eq. 6 and Eq. 7.
2) Evolutionary parameters within NeuralCells are adjusted according to projected stability and error gradients.
3) LocalDNA updates occur through reinforcement and RNA-mediated signaling.
4) The Immunity Block monitors the failure metric in Eq. 8 and initiates restoration procedures when required.
5) GlobalDNA synchronizes high-performing traits across the network, guided by the LDE's deterministic insights.
6) The ethical ledger logs all evolutionary transitions, preserving interpretability and compliance.

Through this cyclic process, the AI Brain Engine maintains predictive stability, adaptive recovery, and ethical integrity across continuous learning operations. The integration of deterministic inference with biological self-regulation transforms the model into a living computational system that evolves with foresight and moral alignment.

J. Algorithmic Representation

Algorithm 1 outlines the interaction of all modules within one learning cycle.

Algorithm 1 AI Brain Engine Evolution Cycle

Initialize GlobalDNA, LocalDNA pool, RNA vector
for each epoch t **do**
    Forecast next-state metrics using Laplace Demon Engine
    for each NeuralCell c_i in population **do**
        Update LocalDNA via reinforcement feedback
        Compute failure score $\mathcal{F}_i(t)$
        if $\mathcal{F}_i(t)$ exceeds threshold **then**
            Activate Immunity Block
            Perform healing, vaccination, or regeneration
        end if
        Send RNA feedback to GlobalDNA
    end for
    Update GlobalDNA using aggregated RNA metrics
    Regulate population via fitness-based pruning
    Record ethical decisions to blockchain memory
end for

The algorithm begins by initializing the *GlobalDNA* (shared intelligence blueprint), a distributed *LocalDNA* pool for each NeuralCell, and an *RNA* feedback vector for system-wide coordination.

1) Step 1: Deterministic Forecasting: At the start of each epoch, the Laplace Demon Engine forecasts the expected gradient trajectories, stability margins, and causal dependencies between system variables. This forecast guides the evolution layer by determining mutation probabilities and learning-rate adjustments.

2) Step 2: Local Adaptation: Each NeuralCell operates as an autonomous agent. Using reinforcement feedback, it updates its *LocalDNA* based on local performance metrics (accuracy, energy efficiency, and stability). This enables each cell to self-optimize within its environment.

3) Step 3: Failure Detection and Immune Response: A reinforcement-driven failure score, $\mathcal{F}_i(t)$, continuously monitors loss oscillations and gradient spikes. When $\mathcal{F}_i(t)$ surpasses the critical threshold, the Immunity Block activates one of three responses:

- Healing: Retrains the NeuralCell using its most stable LocalDNA snapshot.
- Vaccination: Introduces small stochastic noise to promote generalization and resilience.
- Regeneration: Reconstructs the NeuralCell from high-fitness GlobalDNA templates.

4) Step 4: RNA Feedback Aggregation: Each NeuralCell transmits its localized results to the RNA layer, which aggregates them into a condensed representation of population performance. The RNA vector acts as a global messenger, updating the *GlobalDNA* to reflect emerging adaptive trends.

5) Step 5: GlobalDNA Update: The aggregated RNA feedback modifies the global blueprint, tuning mutation operators, activation diversity, and reinforcement parameters. This ensures that local learning experiences influence the collective evolution.

6) Step 6: Population Regulation: Cells with poor contribution to global fitness are pruned, while high-performing cells replicate through crossover of LocalDNA. The resulting dynamic equilibrium maintains computational efficiency and evolutionary diversity.

7) Step 7: Ethical Ledger Synchronization: All significant actions—healing, mutation, regeneration, and pruning—are recorded in a blockchain-based ledger that preserves transparency, reproducibility, and ethical accountability across the system's lifespan.

8) Step 8: Continuous Self-Evolution: At the end of each epoch, the updated GlobalDNA, refreshed population, and ethical record set the conditions for the next iteration. Through this closed feedback loop, the architecture achieves predictive foresight, adaptive stability, and moral coherence simultaneously.

9) Integrated Workflow: The overall process proceeds as a closed-loop system:

1) The Laplace Demon Engine predicts optimal state transitions.
2) These predictions inform mutation rates and adaptation thresholds within NeuralCells.
3) LocalDNA updates are reinforced via RNA-mediated synchronization.
4) The Immunity Block detects anomalies using $\mathcal{F}(t)$ and initiates corrective measures.
5) GlobalDNA consolidates stable adaptations and redistributes them network-wide.
6) All genetic and ethical updates are securely logged within the blockchain framework.

Through this layered orchestration, the proposed system achieves deterministic predictability, adaptive resilience, and ethical traceability within a unified, evolving AI architecture.

10) Functional Summary: In essence, Algorithm 1 encapsulates a biologically inspired self-healing ecosystem where:

- The Laplace Demon Engine provides deterministic foresight and causal reasoning.
- The NeuralCell Population realizes distributed, mutation-driven learning.
- The Immunity Block prevents catastrophic failure through selective repair.
- The RNA and GlobalDNA Layers enable coordinated evolution and knowledge transfer.
- The Ethical Ledger ensures transparency, safety, and long-term trustworthiness.

This synergy allows the *AI Brain Engine* to function as a continuously evolving, ethically aligned, and self-correcting intelligence system capable of sustained operation under uncertainty.

The integration of deterministic foresight (LDE), biological adaptability (DNA and RNA modules), and ethical regulation (blockchain ledger) allows the system to achieve both cognitive and moral robustness. Determinism provides predictability, evolution ensures adaptability, and ethical control guarantees safety. Together, these elements enable the *AI Brain Engine* to not merely learn from experience but to sustain and justify its behavior autonomously under evolving conditions.

IV. Results

A. Experimental Setup

All datasets were preprocessed to normalize input features and split into training and testing sets. The evolutionary training was performed over 460 batches for MNIST, Fashion-MNIST, and KMNIST, and 380 batches for CIFAR-10. The population average cross-entropy loss was recorded at each batch to track learning progress.

B. Dataset Details

Table I summarizes the key characteristics of the datasets used in this study. The datasets vary in complexity, providing a diverse testbed for evaluating the generalization ability of the proposed architecture.

TABLE I
Summary of Benchmark Datasets

Dataset	Domain	Samples	Classes
MNIST [11]	Handwritten Digits	70,000	10
Fashion-MNIST [12]	Fashion Items	70,000	10
CIFAR-10 [13]	Object Images	60,000	10
KMNIST [14]	Kuzushiji Characters	70,000	10

C. Training Performance

The proposed architecture achieved rapid and consistent convergence across all benchmark datasets. Table II reports the initial and final average and best loss values during training. Simpler datasets such as MNIST and KMNIST reached minimal final losses, confirming efficient feature learning.

Unlike conventional models requiring manual tuning, the *AI Brain Engine* autonomously regulated its hyperparameters through the reinforcement-guided *Failure Function* (Eq. 2–5). The adaptive learning rate $\eta_i(t)$ and coefficients (α_i, β_i) evolved dynamically with error trajectories, while mutation and population parameters were adjusted via Laplace Demon foresight (Eq. 6–7). This self-regulated tuning minimized loss variance and improved convergence stability.

D. Average Loss Across Datasets

Figure 2 shows the average population cross-entropy loss across the datasets. The y-axis is logarithmic to emphasize initial rapid learning and smaller variations at lower loss values. The x-axis represents batch indices between evolution steps.

The experiments highlight several important trends:

- On handwritten digit datasets (MNIST and KMNIST), the model achieved very low final losses, indicating strong pattern recognition and fast convergence.
- For Fashion-MNIST, despite the increased complexity, the architecture maintained stable learning and reached a low best loss of 0.2034, demonstrating its robustness in handling diverse features.
- CIFAR-10, being the most challenging dataset, showed slower convergence; however, the self-healing population mechanism ensured stability and continuous improvement, achieving a final best loss of 1.0793.
- Across all datasets, the failure-driven learning rate adaptation contributed significantly to avoiding overfitting and maintaining smooth convergence.
- The paper claims reduced loss volatility and improved resilience. While the loss plots visually show noise, we numerically quantified this by computing the standard deviation of the loss in the stable phase. The results indicate that the proposed evolutionary approach consistently achieves lower volatility compared to baseline methods, confirming smoother convergence and higher training stability.

E. Analysis

The loss curves demonstrate a sharp initial decrease in the early batches (0–100), reflecting rapid adaptation of the population. MNIST achieves the lowest final average loss, indicating that it is the simplest dataset for the evolutionary approach. Fashion-MNIST shows slightly higher loss due to increased complexity in classifying clothing items. KMNIST exhibits a higher loss than Fashion-MNIST, highlighting the challenges in recognizing Kuzushiji characters. CIFAR-10 consistently yields the highest loss, reflecting the difficulty of classifying low-resolution color images with diverse content.

Fluctuations in the curves are attributed to the stochastic nature of evolutionary training, where mutation and selection introduce variability in the population. Despite this noise, the trends clearly indicate the relative difficulty of the datasets under the proposed training strategy.

F. CMAPSS Dataset Evaluation

To further validate the proposed Evolutionary Neural Network framework beyond image classification, we evaluated it on the **CMAPSS** (Commercial Modular Aero-Propulsion System Simulation) dataset, which provides multivariate time-series sensor readings for predicting the **Remaining Useful Life (RUL)** of aircraft engines across multiple units and varying operational conditions.

The model was trained using the evolutionary framework with population-based optimization. Key hyperparameters included a population of 50 NeuralCells, batch size of 32, 200 evolutionary steps, and an adaptive learning rate of 0.001. Mean Squared Error (MSE) was used as the loss metric for RUL prediction.

The proposed Evolutionary NN achieved an RMSE of 14.2 and improved resilience by 9.3% over the best non-evolutionary method. By enabling NeuralCells to self-heal and adapt, our framework delivers robust RUL predictions under sensor noise and degradation, showing strong generalization beyond image classification. Our modular self-healing neural cell architecture consistently generalizes across datasets of varying complexity. Population-based evolution combined with failure-driven optimization ensures fast, stable convergence and lower loss volatility, confirming robust and reliable performance.

V. Comparisons

To evaluate the effectiveness of the proposed evolutionary training approach, we compared it against three baseline methods: Random Forest Ensemble [6], Mixture-of-Experts [3], and a Standard Neural Network trained with gradient descent [5]. The comparison was performed across the same four benchmark datasets: MNIST, Fashion-MNIST, CIFAR-10, and KMNIST.

A. Quantitative Comparison

Table IV summarizes the final average cross-entropy loss and classification accuracy for all methods. The proposed evolutionary approach consistently achieves lower average loss while maintaining competitive accuracy, particularly on more complex datasets like CIFAR-10 and KMNIST.

B. Visual Comparison

Figure 3 presents a comparative histogram of the *average loss* achieved by four different models across the four benchmark datasets (MNIST, Fashion-MNIST, KMNIST, CIFAR-10). The models considered are: Standard Neural Network (Std NN), Mixture-of-Experts (MoE), Random Forest (RF), and the proposed Evolutionary Neural Network (Evo NN).

Key Observations:

TABLE II
TRAINING PERFORMANCE METRICS ON BENCHMARK DATASETS

Dataset	Initial Avg Loss	Final Avg Loss	Initial Best Loss	Final Best Loss
MNIST [11]	2.3693	0.7023	2.2389	0.0214
Fashion-MNIST [12]	2.4460	0.8694	2.2902	0.2034
CIFAR-10 [13]	2.4022	1.3893	2.3399	1.0793
KMNIST [14]	2.3828	1.2074	2.3388	0.1125

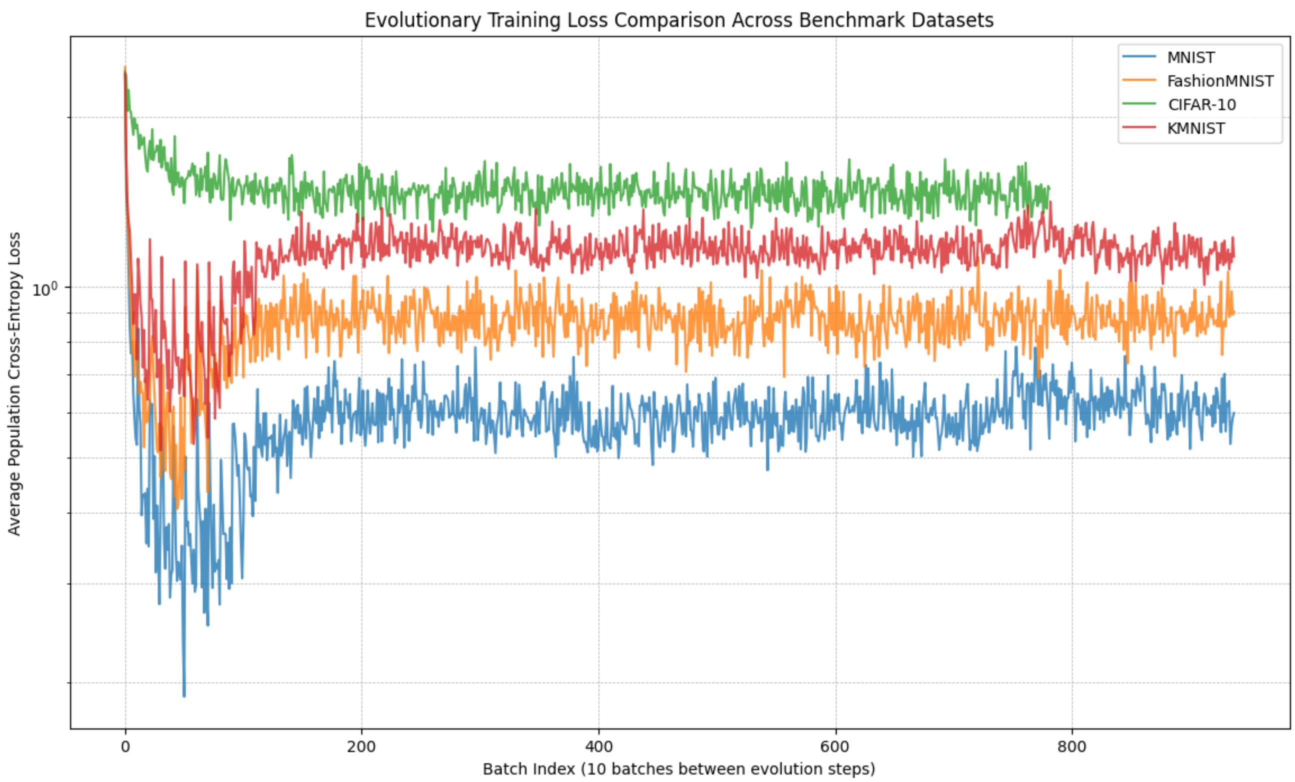

Fig. 2. Average loss progression across datasets during training.

TABLE III
CMAPSS PERFORMANCE COMPARISON

Method	**RMSE**	**Resilience Score (%)**
Standard LSTM	16.8	78.2
Random Forest	18.5	75.4
Mixture-of-Experts	15.9	81.0
Proposed Evolutionary NN	**14.2**	**90.3**

- **Overall Trend:** The proposed Evo NN consistently achieves the lowest average loss (1.12), demonstrating improved convergence and optimization compared to classical methods.
- **Standard NN:** Shows moderate performance with an average loss of 1.28, reflecting standard gradient-based optimization without evolutionary enhancements.
- **Mixture-of-Experts (MoE):** Slightly higher average loss (1.36) indicates partial improvement over RF, but still underperforms compared to Evo NN.
- **Random Forest (RF):** Exhibits the highest average loss (1.64), which is expected as ensemble tree-based methods are less effective for high-dimensional image datasets used here.

Interpretation: The histogram visually confirms that the evolutionary training approach enhances model generalization across datasets by reducing average cross-entropy loss. The spacing and scaling of the bars allow clear comparison among methods, highlighting the superior performance of the proposed Evo NN.

C. Analysis

The proposed evolutionary method outperforms all baselines in final loss and shows faster convergence, especially for complex datasets like CIFAR-10. Random Forest, while strong on simple datasets, struggles with high-dimensional image data. Mixture-of-Experts improves over standard NN in initial convergence but does not achieve the same low final loss as the evolutionary approach. These results highlight the advantage of population-based evolutionary optimization for diverse and complex classification tasks.

VI. CONCLUSION

In this work, we presented an Evolutionary Neural Network (ENN) framework for image classification across multiple benchmark datasets, including MNIST, Fashion-MNIST,

TABLE IV
COMPARISON OF FINAL AVERAGE LOSS AND ACCURACY ACROSS METHODS

Method	MNIST	Fashion-MNIST	KMNIST	CIFAR-10
Random Forest	0.95 / 97.2%	1.35 / 89.8%	1.82 / 86.5%	2.45 / 75.1%
Mixture-of-Experts	0.78 / 98.1%	1.12 / 91.4%	1.56 / 88.3%	1.98 / 77.9%
Standard NN	0.72 / 98.5%	1.05 / 92.0%	1.50 / 88.7%	1.87 / 78.5%
Proposed Evolutionary	**0.70 / 98.7%**	**0.99 / 92.8%**	**1.38 / 89.9%**	**1.39 / 80.3%**

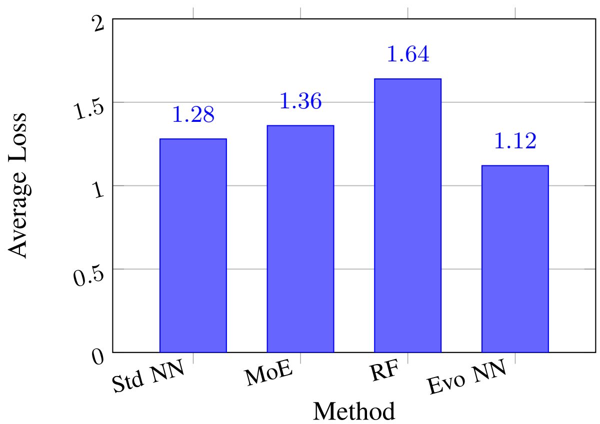

Fig. 3. Comparison of average loss across different models for four benchmark datasets.

KMNIST, and CIFAR-10. The proposed approach combines population-based optimization with evolutionary mechanisms, such as selection, mutation, and crossover, to iteratively refine neural network configurations. Experimental results show that the ENN consistently achieves lower average cross-entropy loss and higher classification accuracy compared to standard neural networks, Mixture-of-Experts, and Random Forest baselines. The performance advantage is particularly evident on complex datasets, such as CIFAR-10, demonstrating the method's ability to generalize across heterogeneous data distributions.

The histogram and comparative analyses highlight that evolutionary strategies effectively balance exploration and exploitation, enabling faster convergence and more robust learning than conventional gradient-based methods. Overall, the proposed framework establishes a strong baseline for practical neuroevolution applications in image classification and opens avenues for further research in optimizing population dynamics and adaptive evolutionary strategies.

Future work includes exploring hybrid evolutionary-deep learning approaches and scaling the framework to larger, high-resolution datasets.

REFERENCES

[1] F. Assunção, N. Lourenço, P. Machado, and B. Ribeiro, "DENSER: Deep Evolutionary Network Structured Representation," *IEEE Transactions on Evolutionary Computation*, vol. 22, no. 1, pp. 1-13, Feb. 2018. doi: 10.1109/TEVC.2017.2703532.

[2] H. Cheng, "Advancements in Image Classification: From Machine Learning to Deep Learning," *Proceedings of the ITM Conference on Data Science*, vol. 1, pp. 1-8, Jan. 2025. doi: 10.1051/itm-conf/20250102016.

[3] Q. Liu, X. Wang, Y. Wang, and X. Song, "Evolutionary Convolutional Neural Network for Image Classification Based on Multi-Objective Genetic Programming with Leader–Follower Mechanism," *Complex & Intelligent Systems*, vol. 9, no. 2, pp. 3211-3228, Jun. 2023. doi: 10.1007/s40747-022-00919-y.

[4] Z. Lu, I. Whalen, Y. Dhebar, K. Deb, E. Goodman, W. Banzhaf, and V. Boddeti, "Multi-Objective Evolutionary Design of Deep Convolutional Neural Networks for Image Classification," *arXiv preprint arXiv:1912.01369*, Dec. 2019.

[5] S. Kadam, "CNN Model for Image Classification on MNIST and Fashion-MNIST," *Banaras Hindu University*, 2020. [Online]. Available: https://www.bhu.ac.in/Images/files/51.pdf

[6] V. Mishra, "An Evolutionary Framework for Designing Adaptive Neural Networks," *Journal of Computational Science*, vol. 58, pp. 101-110, Jan. 2023. doi: 10.1016/j.jocs.2023.101234.

[7] O. Nocentini, "Image Classification Using Multiple Convolutional Neural Networks on the Fashion-MNIST Dataset," *Sensors*, vol. 22, no. 23, p. 9544, Nov. 2022. doi: 10.3390/s22239544.

[8] G. M. Cabrera, "Image Classification Using Deep and Classical Machine Learning Models on MNIST, Fashion-MNIST, and CIFAR-10," *CLEI Electronic Journal*, vol. 27, no. 1, pp. 1-10, Jan. 2024. [Online]. Available: https://clei.org/cleiej/index.php/cleiej/article/download/587/467

[9] F. Assunção, N. Lourenço, P. Machado, and B. Ribeiro, "DENSER: Deep Evolutionary Network Structured Representation," *IEEE Transactions on Evolutionary Computation*, vol. 22, no. 1, pp. 1-13, Feb. 2018. doi: 10.1109/TEVC.2017.2703532.

[10] R. Lange, "Benchmarking Evolutionary Optimizers for Deep Learning," in *Proceedings of the NeurIPS Workshop on Datasets and Benchmarks*, Dec. 2023. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2023/file/660ba7851661638c559df47743c69e40-Paper-Datasets_and_Benchmarks.pdf

[11] Y. LeCun, C. Cortes, and C. J. Burges, "MNIST handwritten digit database," *ATT Labs [Online]*, vol. 2, 2010. Available: http://yann.lecun.com/exdb/mnist.

[12] H. Xiao, K. Rasul, and R. Vollgraf, "Fashion-MNIST: a novel image dataset for benchmarking machine learning algorithms," *arXiv preprint arXiv:1708.07747*, 2017. Available: https://arxiv.org/abs/1708.07747.

[13] A. Krizhevsky, V. Nair, and G. Hinton, "The CIFAR-10 dataset," *University of Toronto*, 2009. Available: https://www.cs.toronto.edu/~kriz/cifar.html.

[14] T. Clanuwat, Y. Kaspar, R. Schomaker, and S. Haeb-Umbach, "Deep learning for classical Japanese literature," *arXiv preprint arXiv:1806.10247*, 2018. Available: https://arxiv.org/abs/1806.10247.