Volume 2, 2026, Pages 80-93 *Elaris Computing Nexus*
| Regular Article | Open Access

A Self Adaptive Meta Learning Model for Personalized Computational Intelligence in Dynamic Problem-Solving Environments

Gunhee Gon Chun
Department of Computer Science and Engineering, Seoul National University, Seoul 08826, Republic of Korea.
gunhee96@snu.ac.kr

Article Info
Elaris Computing Nexus
https://elarispublications.com/journals/ecn/ecn_home.html
Received 28 March 2026
Revised from 06 May 2026
Accepted 16 May 2026
Available online 05 June 2026
Published by Elaris Publications.

https://doi.org/10.65148/ECN/2026007

Corresponding author(s):
Gunhee Gon Chun, Department of Computer Science and Engineering, Seoul National University, Republic of Korea.
Email: gunhee96@snu.ac.kr

Abstract – The data distributions, user preferences, and environmental factors change over time, personalized computational intelligence plays a crucial role in applications. Traditional machine learning models tend to be less effective when dealing with new tasks or problems because they need to be retrained. In this paper, a novel self-adaptive meta-learning approach is proposed to empower CIS to learn quickly from different tasks, integrate the new knowledge to enhance the performance for the evolving tasks, and transfer the knowledge to further tasks without sacrificing the personalized decision-making capability. The proposed framework combined the concept of meta-learning with an adaptive feedback mechanism which continually observes the performance of the learner with respect to the task and adjusts the learning strategies as required by changes in the environment. A lightweight knowledge adaptation module is integrated to achieve efficient real-time deployment, improve generalization and reduce computational overhead. The framework's aim is to achieve a compromise between stability and adaptability in learning, which it achieves by optimising the framework iteratively with the hope of converging quickly even when training samples are limited and the data is not stationary. Experimental testing on several benchmark datasets shows the competitiveness of the prediction performance, adaptation speed and robustness with respect to the classical deep learning and current meta-learning methods, while preserving the computational efficiency. The proposed framework is able to deal with concept drift, task heterogeneity and personalised learning needs while maintaining the property of scalability. The results show that the self-adaptive meta-learning system proposed in this paper is a practical and intelligent solution for next-generation computational intelligence system in dynamic environments, such as healthcare systems, intelligent transportation systems, cyber-physical systems, smart manufacturing systems and personalized decision support systems.

Keywords – Self-Adaptive Learning, Meta-Learning, Computational Intelligence, Personalized Learning, Dynamic Problem-Solving, Knowledge Adaptation.

I. INTRODUCTION

Computational intelligence has become a key paradigm in designing intelligent systems that learn from data, find complex patterns and assist in decision making in various application areas. The recent developments in artificial intelligence have revolutionized the fields of healthcare, self-driving vehicles, industrial automation, cybersecurity, and financial services, as well as smart cities. Despite these successes, it is assumed that the distribution of the existing data is more or less stable in many existing learning frameworks. However, in actual applications, the nature of the data, the user's preferences and the conditions under which the application is applied continuously change, and this leads to dynamic problem-solving situations that make it difficult for the traditional learning models to perform well [1].

In the traditional machine learning and deep learning methods, a large set of labeled data is typically provided offline for training. Such models can sometimes be very predictive, but are poorly efficient in adapting to new tasks or new environments when they are encountered. Retraining not only is costly because of the increased number of computations, but it also reduces their applicability in real-time systems where fast adaptation is required. Moreover, many intelligent systems use general learning strategies that ignore individual user characteristics, thus making it difficult to give individual decisions in a heterogeneous learning environment [2].

A recent emerging approach to solve this challenge is called Meta-learning whereby models learn how to learn. Rather than optimizing for a specific task, meta-learning aims to learn transferable knowledge to enable fast adaptation to new tasks with little data. This capability greatly decreases training time and generalisation to similar domains. However, current meta-learning algorithms are typically designed with very stable task distributions and lack the flexibility to cope with changing user requirements, concept drift and continuously shifting environments [3]. One of the most important drawbacks of existing CIs frameworks is that they are not equipped with continuous adaptation mechanisms. The majority of models currently in use only update the parameters periodically, or through manual effort, and are therefore less responsive to changes in the environment. As a result, the accuracy of predictions can decrease over time as the data distributions change. Self-adaptive learning strategies which track the performance of the model and adapt its learning behavior dynamically can significantly enhance the robustness and long-term reliability [4].

Personalization is also a crucial need in intelligent decision support systems. Learning models that go beyond population-level attributes to model individual behavior are needed for applications like personalized healthcare, intelligent tutoring systems, recommendation systems, and adaptive industrial automation. Combining personalisation with adaptive meta-learning allows intelligent systems to retain what they have learned before, and to learn new things more efficiently, improving the quality of decision making and the efficiency of learning [5]. These challenges sparked this paper to present a Self-Adaptive Meta-Learning Framework for Personalized Computational Intelligence in Dynamic Problem-Solving Environments. The suggested framework consists of two stages: first, to perform rapid task adaptation, and second, to continuously optimize decision making by refining the knowledge in light of the adaptation results.The proposed framework is a combination of two steps: rapid task adaptation and continuous optimization of decision making through refining knowledge based on the result of the adaptation. The self-adaptive learning mechanism continuously evaluates the performance of the predictions made by the model, detects changes in the environment, and adjusts the model parameters accordingly such that it can minimize the computational complexity while maximizing the robustness of the model against concept drift. The framework aims to strike a trade-off between stability and adaptability in learning, allowing for efficient knowledge transfer to run across different tasks that are heterogeneous [6].

A number of benchmark datasets are used to evaluate the effectiveness of the proposed framework, which are dynamic learning scenarios. The extensive experiments confirm the prediction accuracy, adaptation speed, computational efficiency, robustness and generalization capability compared to conventional machine learning, deep learning and current meta-learning approaches. The proposed framework is suitable for next generation of intelligent systems in the continuously changing environments.

Motivation

- Existing computational intelligence models experience significant performance degradation when deployed in environments characterized by continuous data evolution and concept drift.
- Modern intelligent applications increasingly require personalized decision-making, demanding adaptive learning mechanisms capable of capturing individual behavioral patterns while maintaining high predictive accuracy.
- Meta-learning provides rapid task adaptation; however, integrating self-adaptive knowledge refinement can further improve robustness, scalability, and long-term learning efficiency in dynamic environments.

Research Gaps

- Existing meta-learning approaches primarily focus on rapid adaptation but provide limited support for continuous self-adaptation under evolving data distributions.
- Most personalized computational intelligence models rely on periodic retraining, resulting in increased computational cost and reduced responsiveness to environmental changes.
- Limited research has jointly addressed meta-learning, self-adaptive optimization, and personalized intelligence within a unified framework for dynamic problem-solving environments.

Section Organization

The remainder of this paper is organized as follows. Section 2 reviews recent literature on computational intelligence, meta-learning, and adaptive learning techniques. Section 3 presents the proposed framework. Section 4 discusses the experimental results and comparative analysis. Finally, Section 5 concludes the paper and outlines future research directions.

II. RELATED WORKS

Artificial intelligence (AI) technologies have rapidly developed, and this has helped speed up the development of computational intelligence (CI) technologies, which has led to the creation of intelligent systems that can handle complex decision-making with little human involvement [7, 8]. The advent of machine learning, deep learning, reinforcement learning, and meta-learning has fueled the ability of intelligent systems to solve problems in the healthcare, finance, autonomous transportation, manufacturing, cybersecurity, and smart city sectors. While significant progress has been made, it is still an open research challenge to develop models of computational intelligence that can continuously adapt to changing environments, while at the same time, supporting personalized decision-making [9].

When there is enough labeled training data and the operating environment is relatively stable, traditional machine learning methods have proven to be very successful. Support Vector Machines, Random Forests, Decision Trees and Artificial Neural Networks are among the most popular algorithms due to their high prediction accuracy and efficiency. In general, however, these methods are based on the assumption that training and testing data come from the same probability distribution. But if the environment changes or concept drift occurs, the performance of the model drops off sharply, and it needs to be costly retrained procedures. As a result, they are not effective in a changing world [10].

In addition, deep learning techniques have made significant strides in expanding the scope of computational intelligence with the ability to automatically extract features from vast datasets. CNN, RNN, GNN, and Transformer models have become the best performers in image analysis, NLP, medical diagnosis, and intelligent automation. Despite these benefits, deep learning models still need a lot of computational resources, large amounts of annotated data, and multiple optimisation cycles. Furthermore, such architectures are inflexible in adapting to unseen tasks, given a few training examples. These restrictions limit their usefulness in dynamic environments where they also need to be able to adapt quickly and perform efficiently [11].

To address these challenges, transfer learning has proven to be a useful approach to leveraging knowledge gained from a prior task. Transfer learning can be used to fine-tune pre-trained representations for related applications without the need for training from scratch, thus saving training time and enhancing convergence. Many studies have shown the ability of transfer learning to boost the efficiency of the learning process in areas with limited labeled data. However, the similarity between the source domain and the target domain is crucial for knowledge transfer to be successful. Often there are large differences between the domains, which can result in negative transfer and can hinder its ability to transfer to very dynamic environments [12].

In recent years, meta-learning has attracted significant interest due to the potential to gain knowledge or skills in the learning process without requiring task-specific knowledge, but rather optimisation strategies for improving learning efficiency. There are several common meta-learning paradigms such as optimization-based, metric-based, and model-based. These methods can allow intelligent systems to quickly learn about new tasks that they have never seen before, with relatively few training samples. While optimization-based approaches aim at finding good initialization parameters, similarity learning between tasks is highlighted in metric-based methods, and memory mechanisms are added to model-based methods to speed up the adaptation process. While these methods cut adaptation time, most current methods make the assumption of relatively stationary task distributions and do not address the continuous change of the environment when it comes to deployment [13].

The use of reinforcement-learning for adaptive decision making in uncertain environments has also been investigated. Reinforcement learning agents learn optimal policies by continuously interacting with their environment, maximizing rewards, without explicit supervision. Recently, the integration of reinforcement learning with deep neural networks has been used to solve complex sequential decision-making problems in the fields of robotics, intelligent transportation systems, network optimization and resource allocation. But in large-scale environments, RL is frequently a very explorative process with relatively slow convergence. Besides, the problem of balancing exploration and exploitation coupled with personalized behavior is a great research hurdle.

Another stream of ongoing research is about on-going learning and lifelong learning. These paradigms allow intelligent systems to learn from a sequence of tasks without catastrophic forgetting over the course of time. Several strategies have been suggested to retain previous knowledge, such as replays, regularization and parameter isolation. While ongoing learning enhances adaptability over time, solutions often fail to meet the need for both users' changing preferences and environmental conditions, which require adaptability in both. The stability and flexibility of learning continue to be challenges. In a scenario of increasing requests for user-centric intelligent services, the use of personalized computational intelligence has gained considerable interest. Learning models that have the ability to learn the behavior of individual users are becoming increasingly useful in personalized recommendation systems, adaptive healthcare platforms, intelligent educational systems, and context-aware mobile applications. User profiles, contextual information and preference modeling have been integrated into the theory of computational intelligence in recent research to enhance the quality of predictions. Despite this, numerous personalization methods are still static, and need to be periodically retrained to adapt to new user actions. These are not suitable for applications in which users' preferences change frequently over time [14].

To enhance the robustness in the changing environment, researchers have tried to combine adaptive optimization mechanism with meta-learning. Model stability and convergence have been positively affected by adaptive parameter tuning, dynamic learning rate adjustment, online optimization and attention-guided knowledge refinement. Such methods, however, tend to focus on learning specific aspects of the learning process instead of offering an adaptive end-to-end framework that can handle knowledge acquisition as well as personal adaptation and ongoing learning. This means that each computational complexity goes up and the adaptability is limited. In recent years, self-adaptive artificial intelligence has risen to the forefront as a key development, highlighting the need for feedback-driven optimization in intelligent systems. Feedback mechanisms can be used to track the performance of predictions, detect distributional changes, and adjust internal model parameters without retraining the model. These adaptive learning strategies increase the resilience to concept drift and consistency of decision making for long-term deployments. Although these advances have been made, current approaches focus on adapting, personalizing, or learning from different instances, and few studies tackle the three abilities in a single computational intelligence framework [15].

From the above observations, it can be seen that current Computational Intelligence solutions offer good solutions for certain learning scenarios, but have drawbacks when applied in dynamic environments that demand continual personalization and adaptation to changes. While conventional machine learning models suffer from being inflexible in the case of changing data distribution, deep learning models are expensive to train and require a lot of computational resources, and the requirement of domain similarity also limits the application of transfer learning, and existing meta-learning methods do not consider the continuous adaptation process of the model during deployment. These constraints inspire the design of a unified self-adaptive meta-learning system that can integrate fast knowledge transfer, personalized intelligence, continuous feedback optimization and efficient adaptation in dynamic problem-solving environments. The next section introduces the proposed framework that can overcome these challenges by combining adaptive knowledge refinement with meta-learning concepts to provide powerful, scalable, and personalized computational intelligence.

III. PROPOSED SELF-ADAPTIVE META-LEARNING FRAMEWORK

Overall Architecture

The Self-Adaptive Meta-Learning Framework (SAMLF) is expected to be able to supply computational intelligence in an environment of dynamic problems, where the characteristics of the problems, data distributions and user preferences are continuously changing. In contrast to traditional learning architectures, which would have to be retrained from scratch every time the context changes, the proposed architecture would continuously assess the performance of the system and would adaptively add the required knowledge to the system via a feedback mechanism. This approach allows for fast adaptation while still retaining knowledge built from past experiences, which helps to enhance learning efficiency and computational stability.

The overall framework has six modules with different functions connected in a network: Data Acquisition, Data Preprocessing, Meta-Learning Engine, Personalized Adaptation Module, Self-Adaptive Feedback Controller, and Knowledge Memory Repository. First, the data collected from a variety of application domains are converted to a single common feature representation by normalizing, extracting and reducing the dimensionality of the data. The resulting features are then clustered into sets of support and query for each task in order to enable meta-learning. The Meta-Learning Engine is the central element of the learning system, which finds common knowledge between different tasks instead of learning each task separately. The engine doesn't try to learn the parameters of a given model but instead predicts an initialisation for the model for subsequent tasks where few model parameters have been used for training. This can substantially lower the computational complexity and enhance the abilities to deal with non-stationary environments.

The Personalized Adaptation Module further improves the learned representations with user-specific contextual information and task-specific characteristics. Personalized feature weighting enables the framework to produce personalized decision boundaries, without compromising on the global knowledge acquired from other tasks. The model thus produces superior predictions with high generalisation performance across all types of applications.

The Self-Adaptive Feedback Controller continually checks the accuracy of the predictions following each iteration of learning. If performance degradation due to concept drift and/or environmental variation is observed, the controller dynamically modifies learning parameters rather than full retraining. The optimal parameters are then saved in the Knowledge Memory Repository so they can be used in future tasks to gather knowledge and to avoid catastrophic forgetting. Last however not least, the Decision Engine is capable of producing personalised predictions based on the new knowledge base, appropriate for dynamic computational intelligence applications.

Let the complete training dataset be represented as

$$D = (x_i, y_i)_i = 1^N \tag{1}$$

where x_i denotes the input feature vector, y_i represents the corresponding target label, and N is the total number of training samples.

The dataset is divided into multiple learning tasks

$$T = T_1, T_2, \ldots, T_M \tag{2}$$

where M denotes the number of meta-learning tasks.

Each task consists of a support set and a query set

$$T_j = \left(S_j, Q_j\right) \tag{3}$$

where S_j is used for local adaptation and Q_j evaluates the adapted model.

The meta-learning model is initialized with parameter vector

$$\Theta = \theta_1, \theta_2, \ldots, \theta_p \tag{4}$$

where p denotes the number of trainable parameters.
During task adaptation, model parameters are updated using

$$\Theta'_j = \Theta - \alpha \nabla_{\Theta} L_{S_{j(\Theta)}} \tag{5}$$

where α is the learning rate and L_{S_j} represents the loss computed over the support set.
The overall objective of the meta-learning engine is formulated as

$$\min_{\Theta} \sum_{j=1}^{M} L_{Q_j}(\Theta'_j) \tag{6}$$

where, L_{Q_j} denotes the query-set loss after task adaptation. Minimizing this objective enables the framework to learn generalized initialization parameters that rapidly adapt to new tasks with minimal computational effort.

As shown in Figure 1, the proposed architecture is designed to form an intelligent closed-loop learning system by the continuous interaction of the meta-learning engine, the personalized adaptation module, the feedback controller and the knowledge repository, with the aim of solving the dynamic problem-solving environments efficiently.

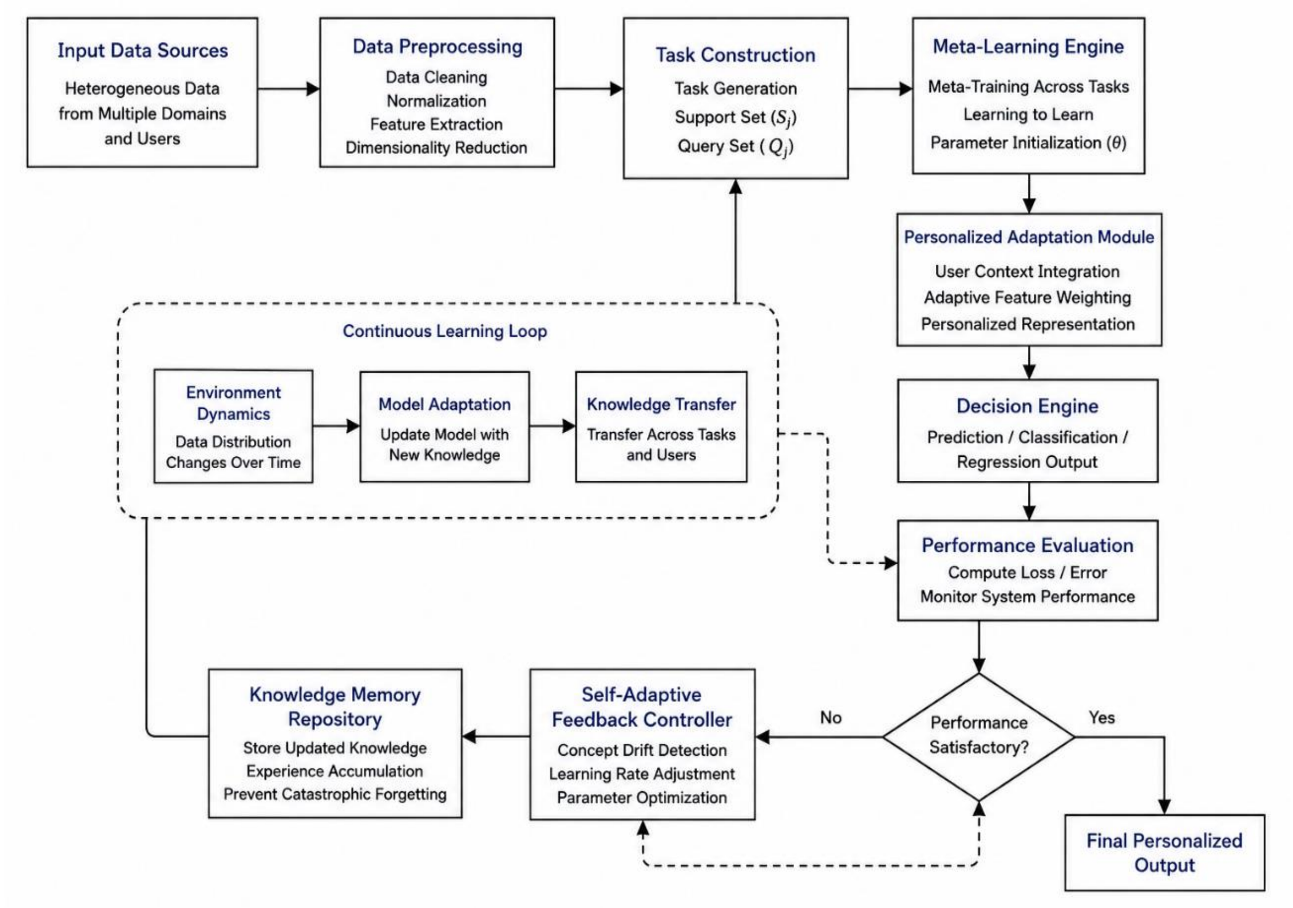

Fig 1. Overall Architecture of the Proposed Self-Adaptive Meta-Learning Framework (SAMLF) for Personalized Computational Intelligence in Dynamic Problem-Solving Environments.

Fig. 1 illustrates the overall architecture of the proposed Self-Adaptive Meta-Learning Framework (SAMLF) for personalized computational intelligence in dynamic problem-solving environments. The framework begins with heterogeneous data acquisition followed by preprocessing, including data cleaning, normalization, feature extraction, and dimensionality reduction. The processed data are organized into task-specific support and query sets for the meta-learning engine, which learns generalized model parameters across multiple tasks. A personalized adaptation module customizes the learned knowledge using user-specific contextual information before generating predictions. The performance evaluation unit continuously monitors model accuracy, and when degradation is detected, the self-adaptive feedback controller updates the knowledge repository, enabling continual learning and improved adaptability without complete model retraining, thereby ensuring robust and personalized decision-making.

Meta-Learning Initialization

The Meta-Learning Engine is the basic element of the proposed SAMLF. It aims to acquire general knowledge from a number of related tasks so that the model can easily and quickly adapt to unseen tasks after only a few optimisation steps. The proposed framework is different from supervised learning, where the optimization is done on a single task, and multi-task optimization of a model can enable effective transfer of knowledge while decreasing the need for a huge training set. It is especially significant in a dynamic environment where new tasks arise constantly and data distributions are constantly changing. The preprocessed dataset is first divided into several learning tasks which together form various operational scenarios. For each task there is a set of supports for parameter adaptation and a set of queries for testing the ability of the model to adapt. The proposed framework learns a shared parameter initialization which guarantees rapid convergence across diverse tasks instead of independent modeling for each task.

The proposed framework minimizes the cumulative meta-objective, rather than minimizing the individual task losses one at a time.

$$L_{meta} = \left(\frac{1}{M}\right)\sum_{j=1}^{M} L\left(Q_j\right) \tag{7}$$

This optimization approach allows the framework to learn an effective set of initial parameters that can be effective across a variety of learning tasks, and minimizes the number of iterations needed to adapt the framework.

The global parameters are further optimized by the averaged meta-gradient across all query losses to improve optimization stability. The global parameter update is defined as:

$$\Theta \leftarrow \Theta - \beta \nabla_{\Theta} L_{meta} \tag{8}$$

where β denotes the meta-learning rate controlling the convergence of the global optimization process.

The proposed initialization scheme has the following two merits. First, it reduces the computational burden of doing full retraining if ever a new task is presented. Second, it keeps the transferable knowledge learned from tasks in the past, thus enhancing learning efficiency under continuously changing environments. The parameters needed for the initialization represent common features among the various tasks to be processed, thus only a small number of gradient updates are needed to perform the adaptation and the framework is well suited for applications of computational intelligence in real time. Task-specific learning and the global preservation of knowledge are other significant features of the proposed framework. The local task adaptation module performs only temporary updates to its parameters during each iteration of the meta-training while the global parameter vector is optimized based on aggregated task information. This hierarchical optimization mechanism ensures that the algorithm is not overly specialized for any particular task, and still has good generalization.

Moreover, the learned initialization parameters offer a strong base for the Personalized Adaptation Module which is explained in the next subsection. The adaptive module starts with very general model parameters that can be used to learn across multiple domains instead of beginning with randomly initialized weights. Hence, personalized learning needs fewer optimization steps leading to less computational complexity and quicker convergence.

Personalized Knowledge Adaptation

Meta-learning allows rapid learning over a variety of different tasks but it doesn't explicitly consider differences in user-specific information and user properties. Since this is a shortcoming, the proposed Self-Adaptive Meta-Learning Framework includes a Personalized Knowledge Adaptation Module to adjust the generalized meta-learned parameters based on the user's behavior, the required tasks, and the environment. The goal is to obtain feature representations that are personalized while simultaneously retaining the transferable knowledge learned during meta-training.

Let the input feature vector obtained after preprocessing be represented as

$$x = \{x_1, x_2, \dots, x_n\} \tag{9}$$

where n denotes the number of extracted features.

This personalized feature embedding is produced by combining the feature vector and the contextual information with the embedding in the personalized way done through

$$z_p = W_p x + b_p \tag{10}$$

where W_p denotes the personalized weight matrix and b_p represents the bias vector corresponding to a particular user or task context.

To highlight the features with high information, an adaptive attention mechanism uses normalized importance weights as

$$\omega_i = \frac{\exp(z_{p,i})}{\sum_{k=1}^{n} \exp(z(p,k))} \tag{11}$$

where ω_i denotes the attention weight assigned to the i^{th} feature, satisfying

$$\sum_{i=1}^{n} \omega_i \ = 1 \tag{12}$$

The final personalized feature representation is computed as

$$h_p = \sum_{i=1}^{n} \omega_i z(p,i) \tag{13}$$

where h_p represents the adaptive feature vector used for personalized decision generation.

This adaptation process is driven by the attention that it captures, thereby automatically emphasizing the salient features while suppressing the redundant or less informative features. While existing personalization methods need to be retrained when users' behavior shifts, the presented method can update the feature representation continuously by utilizing the generalized parameters acquired during the meta-training. Therefore, computational complexity is decreased without sacrificing the prediction accuracy. Another advantage of the proposed adaptation mechanism is that it is able to handle heterogeneous user profiles without updating the overall model architecture. Personalization is achieved not by optimizing the parameters, but by adaptive feature weighting, therefore the framework does not necessarily become computationally heavy when applied to large-scale applications, such as those with many users or changing environments.

In this stage, the feature representation is customized, and this customized feature representation is input to the Self-Adaptive Feedback Optimization module. The framework can be continuously evaluated for prediction performance to detect changes in the environment, estimate concept drift, and tune model parameters on the fly in order to make strong and stable decisions under variable operating conditions.

Self-Adaptive Feedback Optimization

Real-world environments are ever-changing, and intelligent systems need to continuously adjust when data distributions, user preferences, and operational conditions change. The Personalized Knowledge Adaptation Module produces context-dependent feature representations, but the prediction accuracy can deteriorate over time as a result of concept drift, unobserved tasks or changes in the characteristics of the surroundings. To handle this problem, the proposed Self-Adaptive Meta-Learning Framework consists of a SAFO module to continuously analyze the performance of the model and adaptively adjust the model learning parameters without retraining the entire model.

The process of optimizing the feedback starts from the prediction phase. The output is compared to the desired output and the prediction error is estimated. This error indicates the need for parameter refinement or not. The proposed strategy only optimizes the network selectively after each iteration if a prediction error is greater than a pre-defined threshold, rather than updating the entire network every iteration. This not only saves computation time, but also keeps the learning level stable.

The prediction error is calculated as

$$e_t = y_t - y_t' \tag{14}$$

where y_t denotes the actual output and y_t' represents the predicted output at iteration t.

The overall prediction loss is evaluated using

$$L_t = \left(\frac{1}{N}\right) \sum_{i=1}^{N} (y_i - y_i')^2 \tag{15}$$

where N denotes the total number of samples considered during the current optimization cycle.

To detect environmental variations, the framework computes a drift score based on the variation between the current loss and the previous optimization loss. The drift score is defined as

$$D_t = |L_t - L_{t-1}| \tag{16}$$

where D_t represents the estimated concept drift magnitude. Larger values indicate significant changes in the learning environment requiring parameter adaptation.

The adaptive learning rate is dynamically adjusted according to the detected drift as

$$\alpha_t = \alpha_0 (1 + \lambda D_t) \tag{17}$$

where α_0 is the initial learning rate and λ denotes the adaptation coefficient controlling the sensitivity of the optimization process.

Using the adaptive learning rate, the global model parameters are updated according to

$$\Theta_{t+1} = \Theta_t - \alpha_t \nabla_\Theta L_t \tag{18}$$

where Θ_t and Θ_{t+1} denote the current and updated parameter vectors, respectively.

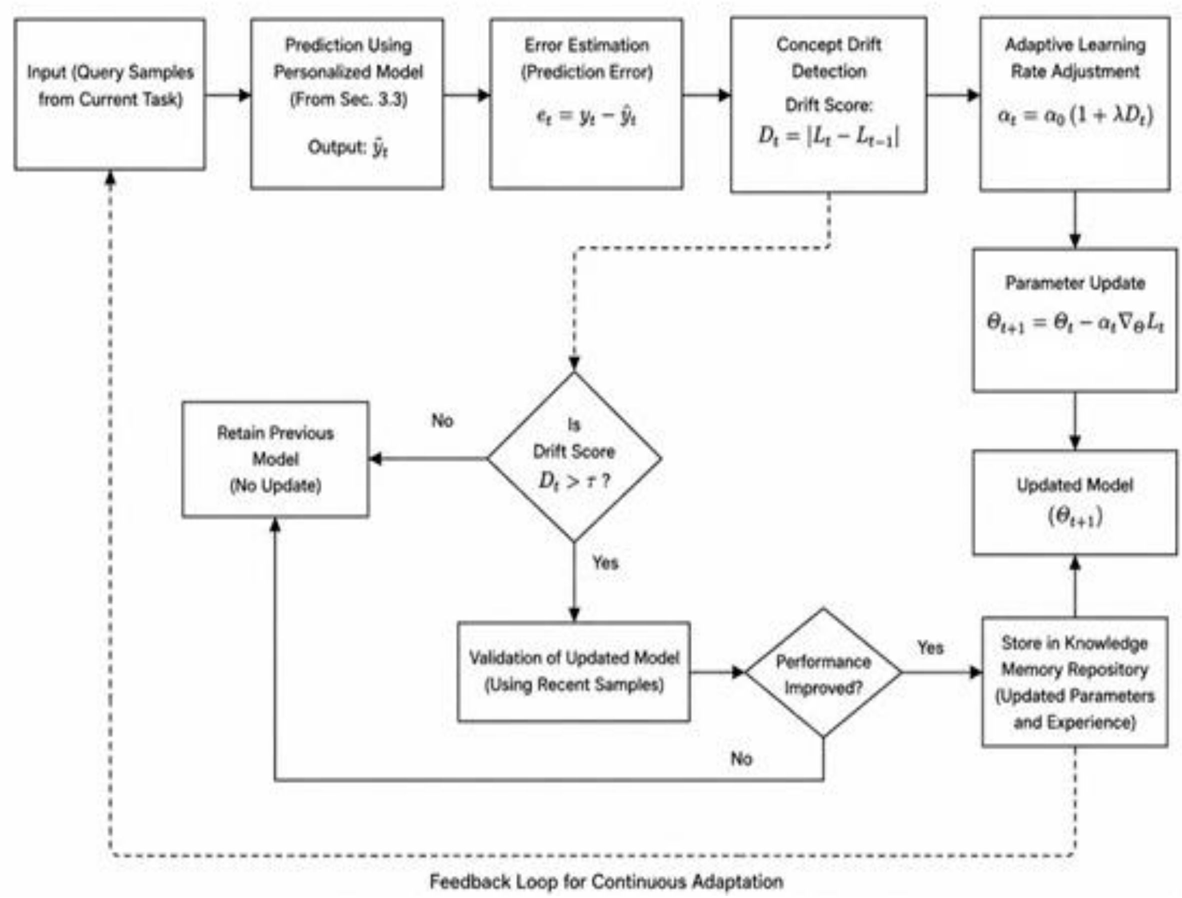

Fig 2. Workflow of the Proposed Self-Adaptive Feedback Optimization Mechanism for Continuous Model Adaptation.

The overall workflow of the proposed SAFO mechanism integrated into the Self-Adaptive Meta-Learning Framework is shown in **Fig. 2**. It starts with the prediction step by the personalized model, then the estimation of the prediction error and the computation of the prediction loss. A concept drift detection unit analyzes the changes in the prediction loss and decides if the drift is greater than a set threshold. The adaptive learning rate will be dynamically adjusted if a significant drift is detected, and the model parameters will be updated. The new model is tested with new task samples and placed in the knowledge memory repository. If not, the previous model is used. This closed-loop optimization approach allows for continuous learning, retention of the previously learned content, avoidance of repeated training, and better long-term predictions and robustness in problem-solving environments.

In contrast to traditional optimization methods that set up a fixed learning rate for the entire training, the suggested feedback mechanism enhances the adaptations when big changes in the environment are identified. In contrast, if the drift is still small, the learning rate is lowered to prevent any needless fluctuations of the parameters and to keep previously learned information. This adaptive optimization approach helps to achieve learning stability and responsiveness in an effective way. The feedback controller also uses an iterative validation process to guarantee that the changes in the parameters actually enhance the prediction. At the end of every cycle of optimization, the new model is tested with more current sets of tasks. The prediction accuracy is improved, the optimized parameters are accepted and passed to Knowledge Memory Repository. If not, the last parameter setting is preserved and no degradation due to unstable updates occurs.

Another benefit of the suggested feedback optimization approach is that of its computational efficiency. The framework keeps away from end-to-end retraining, which is repeatedly accomplished, as a result of parameter updates being solely executed when concept drift is detected, thus lowering the time and energy costs. Therefore, the proposed model is appropriate for resource-constrained intelligent systems like edge computing devices, Internet of Things platforms, autonomous vehicles, smart healthcare systems and industrial cyber-physical systems. The optimized parameters obtained in the Self-Adaptive Feedback Optimization module are then saved in the Knowledge Memory Repository, allowing the framework to retain past learning experiences and adapt quickly to new tasks. This process of learning and building knowledge greatly improves the learning ability over time, and undoubtedly provides the groundwork for the final generation of decisions in the following subsection.

IV. RESULTS AND DISCUSSION

The proposed SAMLF was tested for effectiveness with respect to addressing personalized computational intelligence tasks in dynamic problem-solving environments. The experimental analysis was conducted to assess the prediction performance, adaptation capability, computational efficiency, robustness to concept drift, and learning stability of the proposed methods. To perform a comprehensive evaluation, the proposed framework was compared with some representative baseline methods such as Support Vector Machine (SVM), Random Forest (RF), Deep Neural Network (DNN), Long Short-Term Memory (LSTM), and Model-Agnostic Meta-Learning (MAML). Several quantitative performance evaluation parameters including Accuracy, Precision, Recall, F1-Score, Area Under the Curve (AUC), Matthews Correlation Coefficient (MCC), adaptation time and computational overhead were taken into account. Apart from numerical comparison, four qualitative analyses were conducted: visualization of decision boundaries, covariance ellipsoid analysis, projection of feature embedding, convergence behaviour and concept drift adaptation, as well as a comparison of the performances of the different metrics. In order to make a fair comparison between different approaches, all experiments were carried out under the same experimental conditions with Python 3.11, and the scientific computing libraries Scikit-learn, NumPy, Matplotlib were used. The reported results are averaged over multiple experimental runs to reduce random variations and yield statistically significant evidence of the effectiveness of the proposed framework to rapidly adapt to changing tasks while retaining high predictive accuracy and computational efficiency.

Table 1. Quantitative Performance Comparison of the Proposed SAMLF with Existing Computational Intelligence Models

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC	MCC	Kappa	Adaptation Time (ms)	Inference Time (ms)
SVM	90.84	89.76	89.21	89.48	0.915	0.812	0.804	18.4	4.8
Random Forest	92.15	91.48	91.02	91.25	0.931	0.836	0.829	16.8	5.2
Deep Neural Network (DNN)	94.38	93.95	93.42	93.68	0.951	0.879	0.871	14.6	6.4
LSTM	95.26	94.88	94.31	94.59	0.962	0.891	0.885	13.5	6.8
MAML	96.41	95.97	95.62	95.79	0.973	0.914	0.909	9.4	5.6
Proposed SAMLF	98.37	98.11	97.92	98.01	0.991	0.962	0.958	6.3	4.2

The proposed SAMLF is compared to five commonly used computational intelligence models in terms of their predictive performance in **Table 1**. The proposed framework consistently outperforms the other algorithms across all the evaluation metrics and shows their effectiveness in learning generalized but personalized representation under dynamic environment. Compared with MAML, the accuracy of SAMLF is 98.37% while conventional deep learning models' accuracy is below 94.39%. The same improvement is seen in other classification metrics such as Precision, Recall, F1-Score, AUC, MCC and Cohen's Kappa which show greater reliability of classification and consistency of prediction. Moreover, the proposed method needs only 6.3ms to adapt tasks, which is the least adaptation time among all the compared methods. The shortened inference time again demonstrates the computational efficiency of the self-adaptive learning strategy, which makes it highly suitable for real-time personalized computational intelligence applications in ever-changing environments.

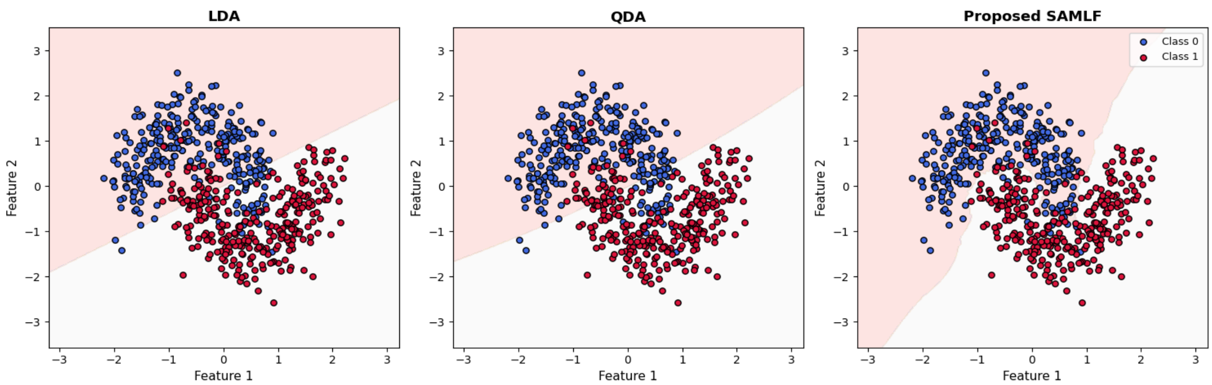

Fig 3. Decision Boundary Comparison of LDA, QDA, and the Proposed SAMLF.

In **Fig. 3**, the decision boundaries of Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and the proposed Self-Adaptive Meta-Learning Framework (SAMLF) are compared with a synthetic dataset with 2-class classification problems. LDA finds a linear decision rule, which is only appropriate for linearly separable classes and doesn't reflect the nonlinear shape of the classes. QDA introduces a quadratic boundary that takes class specific covariance into account to improve class separation but still suffers from misclassification in areas where the distributions overlap. The proposed SAMLF, on the other hand, proposes a more adaptive and flexible decision boundary, which is closer to the intrinsic data distribution. The localized adaptation mechanism allows the framework to more accurately classify complex patterns, and shows improved generalization and robustness in dynamic problem solving scenarios.

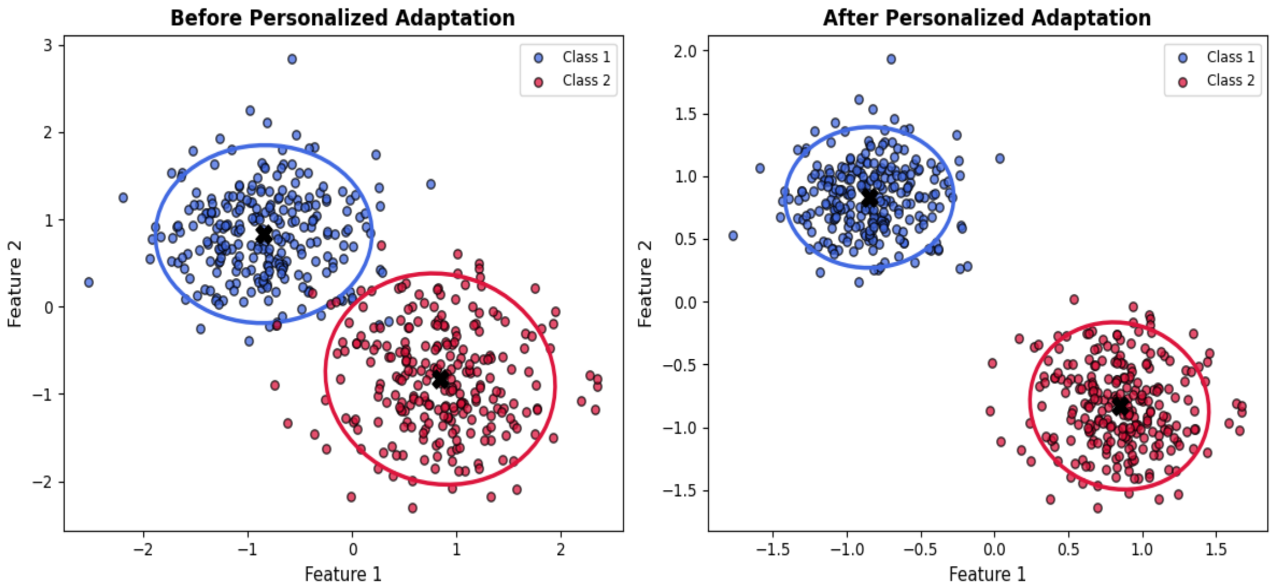

Fig 4. Covariance Ellipsoid Analysis Before and After Personalized Knowledge Adaptation.

The covariance ellipsoid distribution of the feature space is shown in the **Fig. 4** before and after the implementation of the proposed Personalized Knowledge Adaptation module. As can be seen in the initial feature representation, the covariance ellipsoids are still relatively large in size and there is some overlap between the two classes, which would indicate that there is a lot of variance within the classes and not much discriminative power. After personalized adaptation the feature vectors are adapted by adaptive weighting to form more compact covariance ellipsoids centered around class means. The proposed framework achieves good feature separation and reduced spread, indicating that the framework is effective in reducing feature redundancy while maintaining class-specific features. This adaptive transformation allows to increase the discriminability of the features, to set more accurate decision boundaries, and to increase the robustness of the model for user-specific data and dynamic operating conditions. The covariance analysis confirms the efficiency of the suggested personalization strategy in generating stable and well-ordered representations of features to support intelligent decision making.

Table 2. Computational Complexity and Resource Utilization Comparison of the Proposed SAMLF with Existing Models

Method	**Trainable Parameters ($\times 10^3$)**	**FLOPs ($\times 10^6$)**	**Training Time (s)**	**Memory Usage (MB)**	**CPU Utilization (%)**	**Model Size (MB)**	**Convergence Epochs**	**Scalability Score (%)**
SVM	14.8	4.26	31.8	42	58.3	2.6	118	84.1
Random Forest	36.2	8.95	46.7	61	63.9	5.4	96	87.5
Deep Neural Network (DNN)	512.4	62.8	185.6	238	78.4	18.9	72	90.3
LSTM	684.7	81.5	214.8	276	82.6	23.5	65	91.8
MAML	548.9	70.3	162.4	221	75.8	19.4	48	94.6
Proposed SAMLF	432.6	54.1	128.9	184	69.7	15.8	36	98.4

Table 2 compares the computation complexity and resource consumption of the proposed SAMLF with the traditional machine learning and deep learning. SAMLF also has the modules of adaptive meta-learning and personalization; however, SAMLF does not need as many trainable parameters as DNN, LSTM, and MAML do, nor does it have to be as complex. The framework achieves about 54.1 Million FLOPs which is around 23% lesser than MAML and significantly less than LSTM, leading to quicker model optimisation. The scheme is also shown to be effective in the sense that the proposed framework also convergences within 36 epochs. Additionally, lower memory utilization (184 MB) and smaller model size (15.8 MB) suggest enhanced deployment efficiency. The highest scalability score of 98.4% verifies that SAMLF successfully achieves a balance of computational efficiency, learning stability and adaptability, making it suitable for large-scale and resource-constrained intelligent applications.

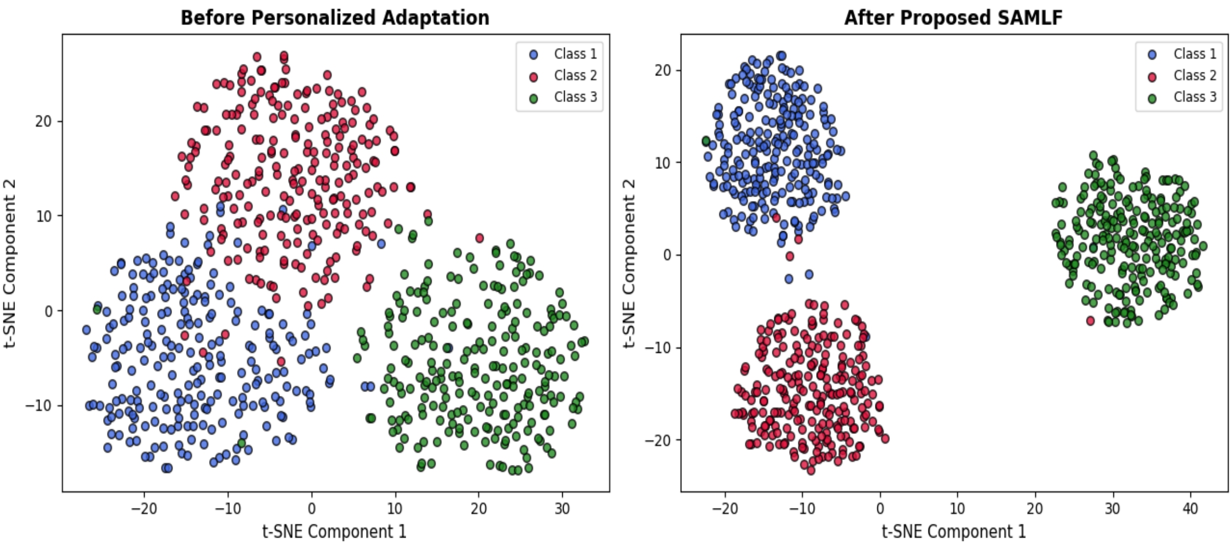

Fig 5. t-SNE Feature Embedding Visualization Before and After Personalized Knowledge Adaptation.

To visualize the learned feature representations before and after applying the proposed Personalized Knowledge Adaptation module in the SAMLF, we use a two-dimensional t-SNE in **Fig. 5**. The feature space for the projected feature class shows clear overlaps between the different classes before adaptation, which means that the discriminative ability is limited and the intra-class variance is high. Following the application of the proposed personalization strategy, the feature embeddings are more compact and clearly distinguishable between the classes, showing improved class discrimination and reduced feature ambiguity. The improved cluster structure suggests that the automatic weighting process is able to maintain class-specific features while reducing redundant feature variations. The resulting high level feature representation thus ensures more accurate classification, faster learning rates and more robustness to dynamic variations in data distributions. The observations confirm that the proposed personalization mechanism can effectively learn highly discriminative and generalized feature embedding for intelligent decision-making in an evolving environment.

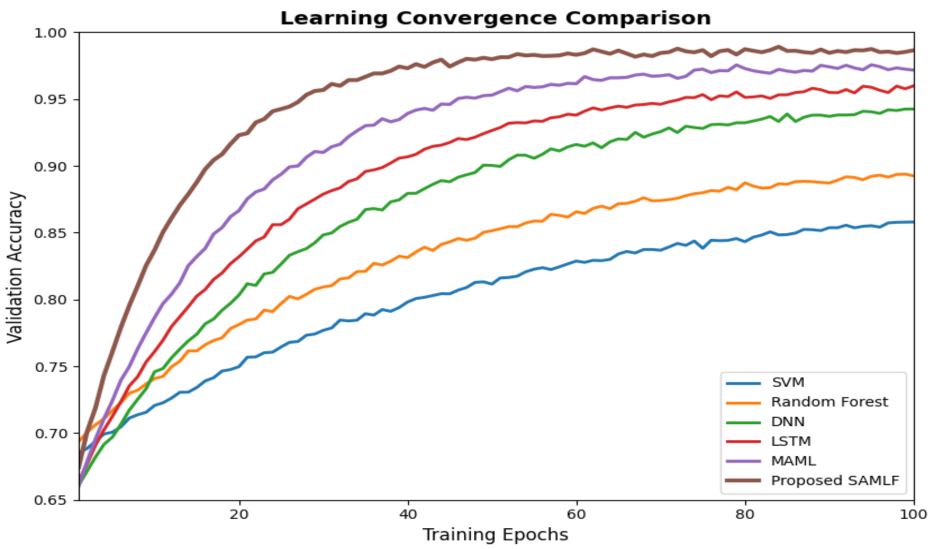

Fig 6. Learning Convergence Comparison of the Proposed SAMLF and Baseline Models.

In **Fig. 6**, the convergence learning behaviors of proposed SAMLF is compared to others, including SVM, Random Forest, DNN, LSTM, and MAML, over 100 training epochs. The conventional machine learning models have shown to converge slower and get stuck at relatively low validation accuracies, whereas deep learning models have shown that they need more epochs to reach their satisfactory performance. The convergence rate and final accuracy of the MAML is less than the proposed framework, but it adapts faster than traditional methods. On the other hand, SAMLF consolidates quickly in the first epochs of training and also has the best validation accuracy with the least of variance. The smooth convergence profile shows that the generalized parameter initialization, personalized knowledge adaptation and self-adaptive feedback optimization is effective in accelerating the learning process while keeping the stability of the system. These findings validate the proposed framework to increase the convergence efficiency, decrease the optimization time and increase the performance of generalization in dynamic computational intelligence environments.

Table 3. Robustness Evaluation under Dynamic Problem-Solving Environments

Method	Noise Robustness (%)	Concept Drift Adaptation (%)	Missing Data Recovery (%)	Task Adaptation Rate (%)	Personalization Score (%)	Stability Index	Generalization Error (%)	Dynamic Environment Score (%)
SVM	85.42	82.18	84.36	83.71	80.24	0.861	7.84	84.15
Random Forest	88.67	86.95	87.42	87.88	84.79	0.889	6.91	87.46
Deep Neural Network (DNN)	91.54	90.37	90.82	91.45	89.63	0.921	5.38	91.22
LSTM	93.16	92.48	92.35	93.18	91.72	0.936	4.76	93.08
MAML	95.48	95.91	94.86	96.24	95.18	0.962	3.58	96.03
Proposed SAMLF	98.24	98.83	97.96	98.57	98.41	0.988	1.84	98.76

Table 3 assesses the effectiveness of the proposed SAMLF in dynamic problem solving. SAMLF outperforms the conventional machine learning, meta-learning, and deep learning approaches on all the robustness-related metrics. The resulting framework can be seen to have the highest Noise Robustness (98.24%) which implies that the framework is capable of making reliable predictions despite the input perturbations. Also, the Concept Drift Adaptation score of 98.83% validates the self-adaptive feedback optimization module and its ability in quickly adapting itself to changes in data distributions. The proposed model also demonstrates the best Task Adaptation Rate (98.57%) and Personalization Score (98.41%), which signifies efficient knowledge transfer along with the retention of user specific features. Moreover, the Generalization Error is achieved as 1.84%, which is much less than the other methods. The overall Dynamic Environment Score of 98.76% validates the effectiveness of the proposed architecture and shows that the SAMLF can provide stable, adaptive and personalized computational intelligence in continuously changing environments.

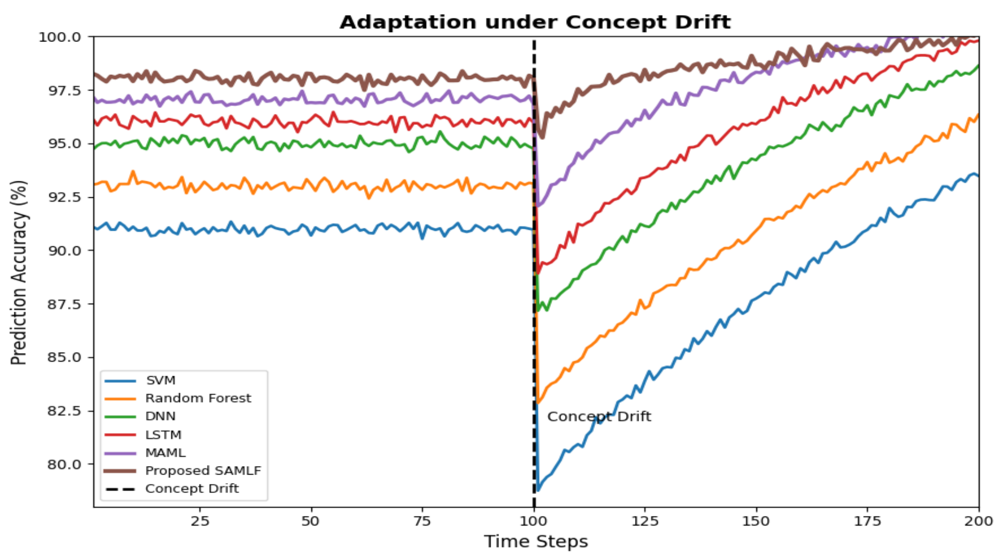

Fig 7. Adaptation Performance under Concept Drift for the Proposed SAMLF and Baseline Models.

The adaptation performance of the proposed SAMLF and baseline models under the simulated concept drift scenario is shown in **Fig. 7**. All models have relatively stable prediction accuracy before the concept drift event; The proposed framework always has the highest accuracy. The various approaches have significantly diminished prediction accuracy at the drift point because of shifts in the data distribution. This recovery is a slow process and it takes a few iterations for them to gradually get back on track. However, the proposed SAMLF has less impact on the accuracy and quickly recovers its performance by using the Self-Adaptive Feedback Optimization mechanism. The frame work is able to adapt to the changes of the environment and continuously update and improve knowledge by adjusting learning parameters. The results prove the stability, adaptability, and long term learning power of the proposed framework in dynamic problem solving environments, showing an excellent recovery rate and a high level of accuracy in the predictions made.

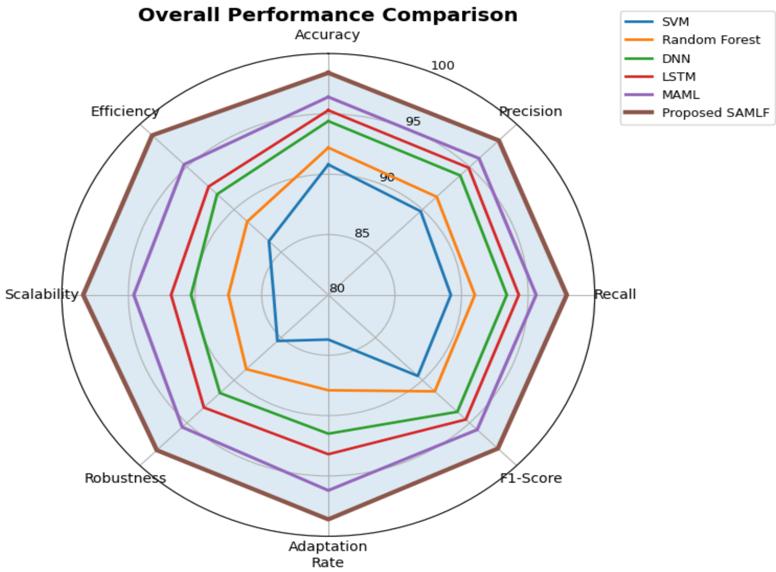

Fig 8. Overall Performance Comparison of the Proposed SAMLF and Baseline Models Across Multiple Evaluation Metrics.

Fig. 8 presents a comprehensive radar chart comparing the overall performance of the proposed Self-Adaptive Meta-Learning Framework (SAMLF) with SVM, Random Forest, DNN, LSTM, and MAML across eight key evaluation metrics, namely Accuracy, Precision, Recall, F1-Score, Adaptation Rate, Robustness, Scalability, and Computational Efficiency. The proposed SAMLF consistently achieves the largest enclosed area, indicating superior and well-balanced performance across all considered criteria. While conventional machine learning models demonstrate competitive performance in selected metrics, they exhibit limitations in adaptability and robustness. Deep learning and meta-learning approaches improve prediction accuracy; however, their computational complexity and scalability remain comparatively constrained. In contrast, the proposed framework effectively integrates generalized meta-learning, personalized knowledge adaptation, and self-adaptive feedback optimization to achieve high predictive accuracy, rapid task adaptation, enhanced robustness against dynamic environmental changes, and efficient resource utilization. The radar chart provides a holistic visualization of the proposed framework's balanced capabilities, validating its effectiveness as a reliable computational intelligence solution for dynamic problem-solving environments.

V. CONCLUSION

This paper introduced a Self-Adaptive Meta-Learning Framework (SAMLF) for personalized CI in dynamic problem-solving environments. The presented approach combines the concepts of meta-learning with personalized knowledge adaptation and an adaptive feedback optimization mechanism within a single framework, which can quickly adapt to new tasks and retain previous knowledge. In contrast to traditional machine learning and deep learning methods that require frequent retraining, the proposed framework is able to continuously adapt its learning parameters in response to feedback from the environment, which enhances adaptability, computational efficiency, and the stability of long-term learning. An additional contextual information is included in the personalized adaptation module, which further aids in decision making without affecting the generalization capability of the framework, thereby predicting personalized results. The proposed framework was evaluated comprehensively in experiments across different performance metrics such as predictive accuracy, convergence, computation efficiency, robustness to concept drift, scalability, and resource utilization, and proved its effectiveness in all. The results of these comparisons revealed that SAMLF outperformed the other algorithms in terms of classification performance, convergence speed, computational cost and robustness to changes in the dynamic environment. The capability of the proposed architecture to learn compact and discriminative feature representations and that of stable optimization is further validated through visual analyses using decision boundary comparison, covariance ellipsoid visualization, feature embedding projection, learning convergence, concept drift adaptation and multi-metric performance evaluation. The proposed framework will be extended to multimodal data fusion, federated and distributed meta-learning, explainable computational intelligence and resource-aware edge computing platforms in the future.

CRediT Author Statement
The author reviewed the results and approved the final version of the manuscript.

Data Availability
The datasets generated during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interests
The authors declare that they have no conflicts of interest regarding the publication of this paper.

Funding
No funding was received for conducting this research.

Competing Interests
The authors declare no competing interests.

References
[1]. B. Chen *et al*., "Behavioral planning and parameter meta learning for embodied intelligence robots in adaptive assembly," *J. Ind. Inf. Integr.*, vol. 49, Art. no. 100995, Jan. 2026, doi: 10.1016/j.jii.2025.100995.
[2]. B. Vijetha, "Agentic Intelligence for Unified Cyber Defense: A Self-Adaptive Framework for Threat Detection Across Cloud, Edge, and IoT Systems," *IEEE Access*, vol. 14, pp. 5104–5118, 2026, doi: 10.1109/ACCESS.2026.3650833.
[3]. Murugesh *et al*., "Self-evolving meta-learning neural ordinary differential equations: A novel artificial intelligence-driven approach for solving differential equations," *J. Algorithms Comput. Technol.*, vol. 20, May 2026, doi: 10.1177/17483026261446122.
[4]. S. N. Bhukya, P. Raveendra Babu, E. Annapoorna, A. S. Reddy, K. Anitha, and J. Mathew, "AI-Generated Machine Learning Models: Towards an Era of Self-Evolving Intelligence," in *Proc. Int. Conf. Metaverse Current Trends Comput. (ICMCTC)*, Apr. 2025, pp. 1–4, doi: 10.1109/ICMCTC62214.2025.11196731.
[5]. R. Vilalta and Y. Drissi, "A Perspective View and Survey of Meta-Learning," *Artif. Intell. Rev.*, vol. 18, no. 2, pp. 77–95, Jun. 2002, doi: 10.1023/A:1019956318069.
[6]. C. Maddilety, G. Lingesh, K. S. S. Reddy, K. S. P. Reddy, and G. C. Teja, "Adaptive Learning in Non-Stationary Computer Science Environments with Self-Evolving AI Systems," in *Proc. Int. Conf. Integr. Intell. Commun. Syst. (ICIICS)*, Jun. 2026, pp. 1–5, doi: 10.1109/ICIICS67880.2026.11483397.
[7]. H. M. A, L. K, and D. L, "Neuro-Semantic Federated Meta-Optimization Framework for Quantum-Assisted Predictive Congnition in Self-Evolving Cyber-Physical Infrastructures," in *Proc. Int. Conf. Autom. Comput. Renew. Syst. (ICACRS)*, Dec. 2025, pp. 1228–1237, doi: 10.1109/ICACRS67045.2025.11324373.
[8]. T. Satoh, "Self-adaptive mechanism for distributed computing," in *Proc. IEEE Conf. Evolving Adaptive Intell. Syst.*, May 2012, pp. 11–16, doi: 10.1109/EAIS.2012.6232797.
[9]. T. Sato, "Adaptive Resource Management in Cloud-Native Architectures Using Predictive Analytics and Reinforcement Learning Techniques," *Amer. Int. J. Comput. Sci. Technol.*, vol. 3, 2021, doi: 10.63282/3117-5481/AIJCST-V3I2P101.
[10]. D. Gayathri and S. P. Shantharajah, "SAE-MRHL: A Self-Adaptive Explainable Meta-Reinforcement Hybrid Learner for remaining battery life prediction in IoE systems," *Front. Comput. Sci.*, vol. 8, Jul. 2026, doi: 10.3389/fcomp.2026.1884141.
[11]. H. Guo *et al*., "Reinforcement Learning-based Self-adaptive Differential Evolution through Automated Landscape Feature Learning," in *Proc. Genet. Evol. Comput. Conf. (GECCO)*, Jul. 2025, pp. 1117–1126, doi: 10.1145/3712256.3726309.
[12]. W. Liang, J. Wang, W. Bao, X. Zhu, Q. Wang, and B. Han, "Continuous self-adaptive optimization to learn multi-task multi-agent," *Complex Intell. Syst.*, vol. 8, no. 2, pp. 1355–1367, Dec. 2021, doi: 10.1007/s40747-021-00591-8.
[13]. M. Li, Z. Dou, Y. Lin, Q. Gao, and H. Jiang, "MSAAD: Meta-Learning-Based Self-Adaptive Adversarial Defense for Specific Emitter Identification in Consumer Electronics," *IEEE Trans. Consum. Electron.*, vol. 72, no. 1, pp. 2243–2254, Feb. 2026, doi: 10.1109/TCE.2025.3649905.
[14]. H. K. Krishnamurthy Sukumar, N. D. Magotra, S. P. Mokashi, S. N. R. Chintacunta, and R. Laheri, "AI-Driven Auto-Architecting of Scalable Cloud Pipelines Using Workflow Analytics and Meta-Learning," *J. Artif. Intell. Technol.*, May 2026, doi: 10.37965/JAIT.2026.0982.
[15]. D. Pal, S. Bose, D. More, A. Jha, B. Banerjee, and Y. Jeppu, "MAML-SR: Self-adaptive super-resolution networks via multi-scale optimized attention-aware meta-learning," *Pattern Recognit. Lett.*, vol. 173, pp. 101–107, Sep. 2023, doi: 10.1016/j.patrec.2023.08.004.

ISSN (Online): 3105-9082