Continual Conscious Active Fine-Tuning to Robustify Online Machine Learning Models Against Data Distribution Shifts

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Abstract—Unlike their offline traditional counterpart, online machine learning models are capable of handling data distribution shifts while serving at the test time. However, they have limitations in addressing this phenomenon. They are either expensive or unreliable. We propose augmenting an online learning approach called test-time adaptation with a continual conscious active fine-tuning layer to develop an enhanced variation that can handle drastic data distribution shifts reliably and cost-effectively. The proposed augmentation incorporates the following aspects: a continual aspect to confront the ever-ending data distribution shifts, a conscious aspect to imply that fine-tuning is a distribution-shift-aware process that occurs at the appropriate time to address the recently detected data distribution shifts, and an active aspect to indicate employing human-machine collaboration for the relabeling to be cost-effective and practical for diverse applications. Our empirical results show that the enhanced test-time adaptation variation outperforms the traditional variation by a factor of two.

Index Terms—Online Machine Learning, data distribution shifts, conscious fine-tuning, robust ML models, next-generation AI, socio-technical human-machine collaboration.

I. INTRODUCTION

The tremendous success of Machine Learning (ML) models is conditioned on the assumption that training and inference time data come from the same distribution. Breaking this assumption, which is the case in many real-world applications, renders ML models susceptible to data distribution shifts. The data distribution shifts occur whenever ML model gets trained on data with a certain distribution and applied to data with a different distribution [1]. It may exist naturally as a result of dynamic changes in the process (common in many real-world ML applications in the wild) or may be induced adversarially for the explicit purpose of compromising the model's performance. Regardless of the source of data distribution shift, the performance of ML models is severely compromised by data distribution shifts. In this work, we address the natural data distribution shifts on the image classification task as a representative proxy for handling different sources of data distribution shifts. Addressing the concern of data distribution shift, effectively and efficiently, is a must to maintain ML models robust and well-performing.

Traditional models (current AI) are the most ubiquitous form of ML models. They have offline settings, in which ML models get trained using offline data and do not get updated at test time. In the offline setting, data distribution shifts are usually addressed by blind retraining, which occurs at different time intervals using a large amount of data. However, this is an inefficient and unreliable retraining process as it is costly and has a low potential to be performed at the right time. Thus, offline-learned ML models are inappropriate for handling distribution shifts effectively. This drawback restricts their use in mission-critical applications. Moreover, we live in an era of ever-changing data and disruptive technologies: IoT, smart cities, cyber-physical systems, metaverse, and industry 4.0 are the most disruptive and promising technologies [2] [3]. That makes addressing offline-learned ML models’ drawbacks more imperative. Researchers and practitioners of ML models should address all the shortcomings in the traditional (offline-learned) ML models to get the most potential of today’s disruptive technologies. They should explore the strategies and learning paradigms that make deployed ML models robust against potential distribution shifts.

A. Current Online Learning Approaches and Limitations

Online learning is a promising research direction that adopts a dynamic training approach to render ML models robust against distribution shifts. The use of dynamic models is recommended, as noted in the research agenda proposed by Ian Goodfellow [1], to make the models robust to distribution shifts. In the online learning paradigm, the learning process is dynamic and models keep updating the model while they are serving at test time. In this work, online learning refers to any learning paradigm in which the model learns at test time. Current online learning paradigms—such as online supervised learning, test-time adaptation, and online active learning—while useful in their own right have important limitations that render them inappropriate for real-world applications such as autonomous driving and visual defect detection.

1) Online supervised learning—in which a learner approaches a predictive task by learning from data stream elements one by one [4] while assuming that the correct
answers will be made available right after the prediction to evaluate and enhance the predictor—is an expensive process that may not always be practical (true labels may not be available or may arrive with a delay) [5].

2) **Test-time adaptation** is another existing online learning paradigm, which is a special variant of unsupervised domain adaptation (see Section I for further details). Although this approach is more cost-effective as it utilizes unlabeled data for the adaptation process, test-time adaptation is restrictive as it cannot sufficiently address drastic data distribution shifts encountered in real-world scenarios.

3) **Online active learning** is a budget-constrained approach which utilizes limited number of labeled data for training a model. Thus, it is a cost-effective learning paradigm. It is adopted when labeling is difficult, time-consuming, or expensive, yet unlabeled data is plentiful and easy to obtain. **Online Active Learning** utilizes the whole set of the relabeled data for retraining the model from scratch. This process has two drawbacks. First, the drastic data distribution shift detection is not incorporated into it. Second, the retraining process requires the availability of the previous data, which is not always available for privacy or commercial concerns. On the other hand, our work is motivated in more realistic scenarios where pre-trained models are not provided with the training data, and the detection and correction of drastic data distribution shifts are addressed utilizing the relevant subset of the relabeled data.

### B. Our Proposed Online Learning Approach

Our work seeks to establish a realistic online learning setting that surpasses existing online learning paradigms. It leverages the potential synergy between the presently disjoint fields of test-time adaptation, online active learning, and transfer learning by fine-tuning for developing practical and robust AI solutions. Typical fine-tuning is used when there is a shortage in the labeled data or for saving the required time and the resources for training a model from scratch. We propose a new online setting that contributes to all these fields. Fig. 1 is a taxonomy that illustrates our work amongst the related learning paradigms.

![Taxonomy of emerging online learning paradigms](image)

**Fig. 1:** A taxonomy contextualizing our work among other emerging online learning paradigms.

To tackle the limitations of the existing online learning paradigms, we propose **Continual Conscious Active Fine-tuning (CCAF)**. It is an ongoing distribution-shift-aware and budget-constrained fine-tuning process that complements test time adaptation to form a new online setting. The learner in this setting aims to adapt to fast-changing environments using both unlabeled and limited labeled inputs to achieve sufficient (application-specific) predictive power and robustness against data distribution shifts. CCAF incorporates continual, conscious, and active aspects: **continual** indicates that models confront the ever-ending data distribution shifts at the test time, **conscious** implies that fine-tuning is a distribution-shift-aware process that occurs at the appropriate time to address the recently detected data distribution shifts, and the **active** aspect indicates employing socio-technical human-machine collaboration for the relabeling to be cost-effective and practical for diverse applications. An abstract illustration of our scheme is presented in Fig. 2, while a more detailed description of CCAF follows in Section III-B.

![Proposed CCAF scheme](image)

**Fig. 2:** Abstract view of the proposed CCAF scheme.

![Enhanced CCAF scheme](image)

**Fig. 3:** An example demonstrating enhanced model performance in an environment with drastic data distribution shifts.

Our proposed scheme is generic and can serve as a baseline for enhancing the robustness against data distribution shifts and improving the training efficiency of the online ML models. Fig. 3 is an abstract example that shows how our work enhances model performance in an environment with drastic data distribution shifts. It illustrates that misclassified inputs drop down when our proposed approach is considered.

The salient contributions of this work are as follows.

- We highlight the weakness of test-time adaptation (TTA) systems in highly changing environments and point out a chance for mitigating it with Continual Conscious Active Fine-tuning (CCAF).
- We suggest a generic online setting scheme that integrates TTA with CCAF to handle drastic distribution shifts in a fast-changing environment.
TABLE I: SUMMARY of RELATED ONLINE LEARNING SCHEMES

| Related Work | Learning Paradigm | Robustness Against Natural Dist. Shifts | Training Efficiency | Suitability for Image Classification Task? | Practical for Real-World Application? |
|--------------|-------------------|----------------------------------------|---------------------|------------------------------------------|-------------------------------------|
| [6] [9]      | Online Supervised Learning | Yes                     | Full Labels         | Continuous Training                      | No                                  | With Costly Monitoring               |
| [8] [10]     | Test-Time Adaptation (TTA) | Partially               | No Labels           | Continuous Adaptation                    | Yes                                 | Insufficient robustness              |
| [11] [12]    | Online Active Learning | No                      | Limited Labels      | N/A                                      | Yes                                 | No                                  |
| [13]         | Transfer Learning By Fine-Tuning | No                   | Limited Labels      | N/A                                      | Yes                                 | No                                  |
| Our work     | CCAF with TTA       | Yes                     | Limited Labels      | Continuous Conscious Active Fine-tuning  | Yes                                 | With Sufficient robustness           |

- We perform extensive simulations to validate the suggested scheme.
- We highlight promising future research directions towards realizing fully online learning in practical settings.

II. RELATED WORK

This section presents the relevant learning paradigms to our proposed work and highlights how our work is different.

A. Online Supervised Learning

Online supervised learning performs the training by incrementally and continuously updating the model on each instance in the data stream. It is robust to data distribution shifts as it handles the worst-case data distribution shift where every single input is a concern. However, being expensive and functionally infeasible for handling tasks such as image classification makes it a restricted learning paradigm. It fits well with a few ML tasks in which the true labels come automatically after some time (e.g., delivery time estimation). The work of Yang and Shami [6] is an example of the works in this research direction, where tabular data is used, and the true labels come automatically after some time. Hoi et al. [4] present further works with online supervised setting. On the contrary, our work achieves robustness against data distribution shifts in a cheaper and more practical setting. It combines limited labels with unlabeled data to provide an online setting that works well with challenging tasks such as image classification. In this work, we differentiate continuous from continual model training. In the continuous mode, the model keeps training after receiving each input in the data stream, while in the continual mode, there is a time interval between consecutive training steps.

B. Test-Time Adaptation Paradigm

Test-time adaptation is an emerging online learning paradigm [8], [10], [4] that utilizes only unlabeled data to continuously adapt the model. It fits the application domains where the ground truths is financially or operationally infeasible. Examples of the adaptation techniques used in this research direction are batch normalization [9], entropy minimization [10], or self-learning [7], [6]. The adaptation techniques incorporated in test-time adaptation may help in maintaining the trained model without retraining for awhile. Specifically, when the environment is not changing drastically. However, they do not sufficiently work when data distribution shift is drastic. Thus, we propose complementing them with continual conscious active fine-tuning to get sufficient performance in scenarios that involve data distribution shifts.

C. Online Active Learning

Previous studies on online active learning such as [11], [12] investigate classification in an IID setting. However, they do not consider the concern of data distribution shift. Moreover, the learning process in online active learning is inefficient. That is, the learner is assumed to have the training data along with the whole set of the selected and relabeled data to perform retraining from scratch. In contrast, our work considers addressing data distribution shifts in a data stream. It contributes to detecting and adapting to multiple data distribution shifts. In addition, our work is more efficient. It utilizes the subset of the relabeled inputs that is relevant to the lately detected data distribution shift.

The degree of data distribution shift can only be identified if we have labeled data to guide the monitoring and evaluation process at test time. However, in many practical settings, full labels are financially and operationally expensive. This limitation calls for budget-constrained and opportunistic online learning techniques to do cost-effective and reliable data relabeling (see Section III-B).

D. Transfer learning by Fine-Tuning

Transfer learning by fine-tuning is well-motivated in situations with abundant training data in a source domain and less data on the target domain. Typical fine-tuning [13] involves one time adaptation of one domain to another. Also, it happens in an offline setting and does not consider data distribution shifts in a fast-changing environment. Although typical fine-tuning occurs by utilizing a small set of inputs, it does not include an active selection process to choose the most informative data for the fine-tuning process. Thus, it is not practical for real-world applications where data distribution shift is a concern and continual budget-constrained adaptation is a must. Contrarily, our work involves conscious active fine-tuning as part of a continual data distribution shift adaptation process. Also, fine-tuning in our work is used to continually adapt the model to multiple domains, i.e., several data distributed shifts. Moreover, our work operates in an online setting and
Fig. 4: Detailed Proposed Scheme. Test-time adaptation (Stage 1) complements CCAF (Stage 2). CCAF strives to consciously generate a fine-tuned model that replaces the trained model when necessary.

it is selective in the data used for the continual fine-tuning process. In other words, the model gets adapted to several data distribution shifts using only the distribution-shift-relevant relabeled inputs.

Existing online learning paradigms are tedious and expensive or do not account for all real-world scenarios where a certain level of robustness against data distribution shift is required. A realistic online setting that is cost-effective and provides sufficient robustness for real-world applications against data distribution shifts is lacking. We propose a generic scheme for online settings to fill this gap. Table I summarizes the limitations and the merits of the learning paradigms related to our suggested online setting. It demonstrates that our proposed learning setting addresses the weaknesses of related learning paradigms.

III. INTEGRATING TEST-TIME ADAPTATION WITH CONTINUOUS CONSCIOUS ACTIVE FINE-TUNING

We present a more detailed view of CCAF in Fig. 4 to expand upon the abstract view presented earlier (Fig. 2). CCAF starts by selecting the most informative inputs, moving them to human experts for validation & relabeling, and then extracting the distribution-shift-related information. After detecting an adaptation insufficiency, human experts consciously decide to fine-tune the trained model in the test-time adaptation stage utilizing the subset of relabeled data that is relevant to the detected type of data distribution shift.

A. Test-Time Adaptation Stage

Test-time adaptation is a process that is achieved through utilizing unsupervised domain adaptation techniques such as entropy-minimization [10] on top of a pre-trained model that does not usually get shipped with its training data. Test-time adaptation stage receives stream of images, processes them, and generates corresponding output confidences as soft predictions. It aims to handle distribution shifts at inference time without the help of labeled data. It is a special type of unsupervised domain adaptation that maps a source (a trained model) to a target (test-time self-adapted model). Test-time adaptation comprises the trained model and an adaptation technique. A self-adaptation technique such as entropy minimization [10] keeps updating very few batch normalization relevant parameters (less than 1%) of the trained model without updating the weights of the model. At test time, a self-adapted model utilizes unsupervised learning approaches to capture the potential out-of-distribution inputs after their first-time prediction. It updates a few parameters of the trained model directly without a retraining process. Thus, the model adapts and correctly predicts the subsequent out-of-distribution inputs.

The most appealing characteristic of this variant of online learning is the relieving of the necessity of having the ground truth labels, which fits nicely in vision tasks where getting the ground truth timely and cost-effectively is a big challenge. However, test-time adaptation techniques are restricted. They
partially help strengthen models against natural distribution shifts such as common corruptions. They do not sufficiently adapt to highly changing environments. That renders those models inappropriate in real-world applications. For that, future AI solutions should consider complementing such approaches with other robust yet cost-effective techniques.

B. Continual Conscious Active Fine-tuning (CCAF) Stage

To maintain the required performance of test-time adaptation, we should have an ongoing monitoring and evaluation process to know the current performance of the model. On the other hand, measuring model performance requires having the true labels of the predicted inputs. For vision tasks such as image classification, true labels cannot be obtained automatically after a specific prediction time as in some other applications such as delivery estimation time. Instead, humans should be involved in validating the predicted inputs, relabeling all predicted inputs, and then retraining the model. Often, it is a tedious, ineffective, and financially infeasible task. Thus, we suggest continual conscious active fine-tuning (CCAF).

By CCAF, we mean that the fine-tuning is a continual, conscious, and active process. Continual fine-tuning means that the fine-tuning is an ongoing process that happens whenever a data distribution shift is detected. Conscious fine-tuning has two aspects (the When and How). In the When aspect, conscious means that the decision of the time of performing a fine-tuning is an informed timing decision because it is not performed blindly but at the time a data distribution shift is detected based on the analysis of the selected and relabeled inputs. Thus, it maximizes the utilization of the allocated budget and the computing resources as it avoids unnecessary fine-tuning. The How aspect of conscious means that the fine-tuning itself is a targeted process because it depends on the subset of the relabeled data that is most relevant to the latest detected data distribution shift. Active fine-tuning means that the detection of data distribution shift is based on an opportunistic selection of the most informative inputs to be validated and relabeled by human experts under a budget-constrained situation. The steps that comprise CCAF are described next.

1) Online Selection: This step involves the reception of a sequence of output confidences from the test-time adaptation stage, processing them, and producing a consciously fine-tuned model. Fig. 4 illustrates the details of the continual process of generating conscious fine-tuned models. In a time interval of a specific time scale (e.g., a day), upon the arrival of a sequence of output confidences along with the corresponding images from Stage 1; utilizing windowing-based online selection techniques, the most informative images (i.e., they have the least confidence) are selected and pushed to the validation process (Step 1 in Fig. 4). In online selection settings where the data stream is never-ending and selected images cannot be revoked, we have to decide on the fly which images to choose for validation and which ones to ignore. We urge considering intelligent and efficient online selection techniques that contribute to efficient utilization of inspection, analysis, and conscious fine-tuning resources. For example, we can use windowing-based online selection techniques such as Opportunistic Selection and Relabeling Algorithm (OSRA) [15].

2) Validation, Relabeling, and Extracting Further Information: This section shows that the socio-technical collaboration between humans and AI contributes to a massive enhancement of AI solutions [16]. The selected images are investigated by humans, i.e., crowdsourced workers. For the image classification task, a human who is assumed to be reliable can judge whether or not the images that come from Stage 1 have correct predictions (Step 2 in Fig. 4) by comparing the actual representation of the image with the predicted label. If there is a mismatch, the crowdsourced worker relabels it, checks the severity level & the corruption type (through comparing the corrupted level with the sample levels found in the benchmarked dataset), and appends the information as a new record in the dedicated table that tracks the distribution shift related information of the relabeled inputs (Steps 3 in Fig. 4). The process of validation, relabeling, and extracting the distribution shift information iterates in a timely fashion (e.g., day).

3) Measuring Model Performance & Analyzing and Deciding a Conscious Fine-Tuning: At the end of a specific time interval, the dedicated table is analyzed to check the rate of the wrongly predicted images to be used as a proxy for the prediction process performance (Step 4 in Fig. 4). If the performance of the model is above a specific threshold (application-specific value), the current model will continue to be utilized. This avoids unnecessary fine-tuning, which prevents unneeded usage of computer resources (computational-wise optimization). On the other hand, if the model’s performance is found below a specific threshold, this indicates the right time for fine-tuning (the “when” aspect of conscious fine-tuning). Then, dedicated table is analyzed further to check the culprits. Culprits are the dominant corruption types and severity levels that contribute to deteriorating the prediction process of the model (Step 5 in Fig. 4). If culprits are found, the output of the analysis phase is an informed decision on how to fine-tune the pre-trained model in Stage 1. That is, the relabeled images with dominant characteristics are chosen consciously to be used in the suggested fine-tuning process. Lastly, the model gets fine-tuned, evaluated, and deployed (Step 6 in Fig. 4).

We note that relabeling has a dual purpose—detection and correction of data distribution shifts. The relabeling process contributes to measuring the rate of the misclassified inputs and accordingly indicates the existence of the data distribution shifts (detection). Also, the relevant relabeled inputs are utilized while performing the fine-tuning process.

IV. Experiments and Results

A. Experimental Setup

To show the effectiveness of our suggested scheme, we simulate several data distribution shifts in a fast-changing environment utilizing RobustBench [17] which is a standard benchmark for evaluating model robustness against natural and adversarial distribution shifts. We utilize CIFAR-10-C, the corrupted version of the standard CIFAR-10 dataset, and
state-of-the-art test-time adapted models such as test-time adaptation by entropy minimization [10]. A simulated input image in CIFAR-10-C is associated with a corruption type and a severity level of the corruption, i.e., the degree of the detected data distribution shift. We simulate five environmental corruption types (fog, snow, frost, contrast, brightness) and five severity levels (1, 2, 3, 4, 5). Higher severity levels are associated with higher distribution shifts.

We simulate two scenarios using the various severity levels and the corruption types of the benchmark. Each scenario represents a potential environment change that a model can encounter in real-world situations.

A scenario is a stream of 1680 images, which is the total images of seven consecutive time intervals (e.g., a week). That is, 240 images in a time interval of a time scale of one day. In the conducted experiments, we allocated a budget of 10% for the human intervention process. One unit of the allocated budget is used for handling one image. That means that the allocated budget is enough for validating and relabelling 10% of images in the stream.

1) Performance Metric: The performance metric we used in our experiments is the rate of misclassified inputs. It is a proxy for the model performance. In our work, we use “model performance” and “robustness” interchangeably to refer to model robustness against natural data distribution shifts.

2) Research Questions: We perform extensive experiments to answer the following questions:

- How does our suggested solution handle drastic data distribution shifts that occur in a constantly changing environment?
- How do windowing-based online selection techniques contribute to the performance of the suggested solution?
- How is the impact of the continual conscious active fine-tuning on test-time adaptation enhancement?

B. Experimental Scenarios

At the end of an investigated time-interval, as detailed in Fig. 4, the model performance is checked. If the measured performance is less than an application-specific required value (e.g., the rate of the misclassified inputs is above 20%), the collected information of the relabeled inputs of the corresponding time intervals is analyzed to find the dominant severity levels and corruption types. This step results in an informed decision of fine-tuning, i.e., conscious fine-tuning. This budget-constrained and conscious fine-tuning is a continual process to ensure a robust and well-performing model even in a fast changing environment.

The first simulated scenario depicted in Fig. 5a refers to a situation where no data distribution shifts are detected in the considered time intervals. Thus, the fine-tuning is not recommended. This scenario demonstrates the best-case situation from the data distribution shift perspective (distribution-shift wise) and the worst-case situation from the budget-utilization perspective (budget-utilization wise). The use of the limited budget in this scenario is justified as a proactive step in real-world application domains where the uncertainty of experiencing distribution shifts is remarkably high.

The second scenario illustrated in Fig. 5b illustrates a potential situation with a highly-changing environment. A new type of drastic distribution shift in each two subsequent time intervals. The conscious fine-tunings have mitigated the risk of model performance deterioration from a complete deterioration in the considered time range to a partial deterioration. Model performance deterioration occurs as a result of data distribution shift. CCAF detects the data distribution shift as soon as it is encountered in a time interval. Then, it consciously recommends performing fine-tuning to avoid model deterioration in subsequent time intervals. This scenario represents the best-case situation (budget-utilization wise) and the worst-case situation (distribution-shift wise).

In all investigated scenarios, the results of our suggested learning paradigm outperformed offline learning (on average) by almost three times and outperformed test-time adaptation by about two times.

C. Windowing-based vs Random-based Selection Strategies

In this section, we aim to show the effectiveness of utilizing windowing-based strategies for selecting the most informative inputs where data distribution shift is a concern. As detailed in
Section [II-E] we adopt the use of these types of strategies in our work. We use the second simulated scenario, as an example, to demonstrate the success rate of selecting the most informative inputs when using both the random-based and windowing-based selection strategies. Fig. 6 clearly illustrates that windowing-based selection strategies outperform random-based selection strategies by a significant margin. Thus, we recommend using windowing-based selection techniques when considering Continual Conscious Active Fine-Tuning for handling data distribution shifts.

**Fig. 6: The rate of the successful selection of the most informative inputs when we utilize windowing vs. random selection algorithms (the higher the better). Windowing outperforms random selection by a significant margin. Thus, we urge utilizing windowing-based selection techniques when considering Continual Conscious Active Fine-tuning.**

**D. Lessons Learned**

- Without utilizing continual conscious active fine-tuning where a drastic data distribution shift is a concern, there is a high potential that a model suffers from longer-time performance deterioration.
- Complementing test-time adaptation with continual conscious active fine-tuning renders test-time adaptation a practical real-world online learning paradigm.
- We urge the online learning research community to utilize windowing-based selection techniques when considering continual conscious active fine-tuning.
- To gain robustness against potential drastic natural distribution shifts, we encourage adopting our suggested online setting scheme (test-time adaptation & continual conscious active fine-tuning).
- CCAF is an ongoing process which means that the corresponding cost of human-machine interaction is also ongoing. For that, our work is worthy when the potential of the occurrence of multiple data distribution shifts is high.
- For the image classification task, the reliable detection and correction of data distribution shifts require expensive human-in-the-loop (HitL) validation and tweaking. Our work optimizes the HitL process so systems owners can utilize it to gain more reliability.
- Detection of data distribution shifts requires investigating at least one-time interval. So, there will always be unavoidable potential exposure to non handled data distribution shift equals one-time interval of a specific time scale. Thus, the shorter the time interval, the better the handling of data distribution shifts.
- Though few online learning paradigms approach better handling of data distribution shifts cost-effectively and under realistic assumptions, they do not provide complete robustness. This problem may continue until AI community makes a breakthrough on the AGI. Only then adaptation process can happen quickly, cost-effectively, and reliably. A practical system that mimics the human vision system is the only approach that can achieve complete robustness against data distribution shifts.

**V. Future Directions**

In this section, we highlight the potential works that might contribute to moving online learning paradigms towards realistic online settings.

**A. Impact on ML Models Security Concerns**

1) **Test-Time Security Concerns:** Traditional ML models are susceptible to various adversarial attacks. For example, they are brittle to adversarial examples. We highly encourage the online learning research community to investigate the impact of our suggested scheme on adversarial robustness. We believe that our generic scheme contributes to adversarial robustness. Our proposed online setting makes the model a moving target. That makes the process of generating adversarial examples more difficult. Suppose an adversary managed to craft an adversarial example during a specific version of the model. In that case, this recently generated attack most probably will not be valid for attacking the model because it would be adapted to a different version due to the defender’s last move advantage.

2) **Training-Time Security Concerns:** A common security concern in ML is training-time attacks. They occur when an adversary manages to access and manipulate the data that will be used for training a model. Since our suggested scheme enhances ML model robustness by utilizing unlabeled data (Stage 1) and limited labeled data (Stage 2), that means that our proposed scheme minimizes the model’s exposure to more labeled data, which is the source of the poisoning attacks. That is because our suggested scheme avoids training from scratch using large labeled data (blind retraining). We believe that studying the impact of our generic scheme on enhancing ML model robustness against test-time attacks is a promising future direction.

**B. Dynamic Windowing for Effective Online Selection**

We think that a sliding window that shrinks and expands dynamically, based on the success frequency of the previous selections, fits well with the online setting of the suggested scheme. Incorporating a dynamic sliding window with our suggested scheme will enhance the scheme’s robustness. Thus, we encourage the online learning research community to investigate the impact of utilizing dynamic windowing in the online selection process on the performance of the suggested scheme.
VI. Conclusion

This work arms the researchers and practitioners of the online learning community with a generic scheme that renders the traditional test-time adaptation approach a practical solution in real-world applications. Test-time adaptation is an emerging cost-effective research direction yet does not sufficiently handle drastic data distribution shifts. We propose an enhanced variation of test-time adaptation that outperforms traditional test-time adaptation. It augments the traditional test-time adaptation with a continual conscious active fine-tuning (CCAF) layer to render it appropriate for handling drastic data distribution shifts. The added layer has a continual aspect to confront the ever-ending data distribution shifts. Its conscious aspect means the fine-tuning should happen at the right time based on an informed decision. The active aspect implies that human-AI collaboration is considered so relabeling becomes cost-effective and feasible for various applications. This work opens the doors for the research community to conduct further research toward more robust and efficient online ML models. Researchers and practitioners can use the suggested generic scheme as a base to explore promising research directions and application scenarios such as training-time security concerns and dynamic windowing for effective online selection.

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