Incremental Cross-Domain Adaptation for Robust Retinopathy Screening via Bayesian Deep Learning

<u>Supporting Material</u>

This document presents the differences between transfer learning, incremental learning, domain adaptation, and the proposed incremental domain adaptation approaches. The fundamental difference between these approaches can be seen in Figure 1. Here, we can notice that in transfer learning (Figure 1-A), the source-domain knowledge is transferred to the target domain to achieve faster convergence for learning the target domain tasks. But after learning the target domain tasks, the network forgets its source domain knowledge. Moreover, in incremental learning (Figure 1-B), the model retains its existing knowledge while learning new tasks where the tasks originate from the same domain. In domain adaptation (Figure 1-C), the network (trained on a source domain) is adapted to one or more target domains where it performs all the inter-related tasks simultaneously across various domain shifts. Contrary to all these approaches, in this paper, we present a novel incremental cross-domain adaptation instrument (Figure 1-D), in which, at first, we constrain the pre-trained model to learn new classification tasks from one target domain incrementally. Afterward, we adapt this model (incrementally) to learn more classification from the second target domain while retaining its previous knowledge, such that the model performs all the cross-modality tasks (related to retinopathy screening) together at the inference stage.

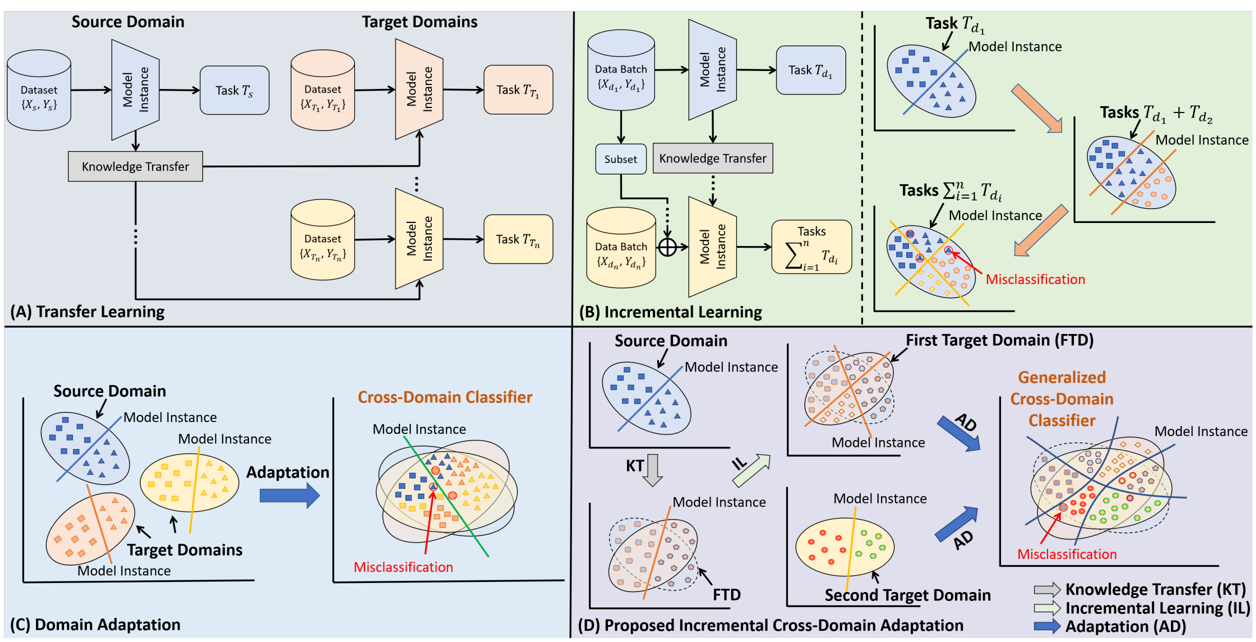

Figure 1: Difference between (A) transfer learning, (B) incremental learning, (C) domain adaptation, and (D) proposed incremental cross-domain adaptation. In transfer learning (A), the source-domain knowledge is transferred to the target domain to achieve faster convergence for learning the target domain tasks. But after learning these (target domain) tasks, the network forgets its understanding of the source-domain (and its related tasks). In incremental learning (B), the model retains its existing knowledge while learning new tasks where the tasks originate from the same domain. In domain adaptation (C), the network (trained on a source domain) is constrained to adapt to one or more target domains to perform similar (and inter-related) tasks across these domains. Different from these paradigms, we present a novel incremental cross-domain adaptation instrument (D) that firstly constrains the underlying pre-trained model to learn new classification tasks from one target domain incrementally. Afterward, it adapts the model (incrementally) to learn more classification tasks from the second target domain, such that the

model can effectively perform all the tasks together at the inference stage. Here, unlike conventional domain adaptation approaches, the proposed scheme allows the classification model to not only learn the similar inter-related cross-domain tasks, but it also constrains the model (via Bayesian inference) to learn new disjoint tasks without forgetting its prior knowledge set.