Continual learning for defect diagnosis of AI-based industrial radiographic testing system using meta learning-based buffer

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Followed by medical arena, manufacturing industries are endeavoring to enhance quality control system by the artificial intelligence to detect defects in Radiographic Testing(RT) images. However, previous system has the critical limitations of being sensitive to domain shifts due to changes in new defect types and changes in the image data distribution acquired from the various shooting condition. Not only is a lot of data required to build a system that is robust to domain changes, but the computational and human resources required to repeat the model training on the data are high. In this study, we propose a novel approach employing continual learning strategies to mitigate training resources with validation based on the industrial RT images. According to previous method, called transfer learning, to reflect new data stream to pre-trained model with fine-tuning weight of parameter a bit. However, this approach presents a challenge known as catastrophic forgetting, wherein the model performance on the previous data stream diminishes due to limited access to the previous during fine-tuning. Therefore, the continual learning strategy must balance between utilizing the limited previous data stream and maintaining performance on that data to avoid catastrophic forgetting. To overcome the catastrophic forgetting, we propose a novel scoring mechanism for selecting samples to be buffered in memory. In the state-of-the-art of continual learning methods, a certain ratio of the previous data stream is buffered memory and reused during the fine-tuning phase to ensure prediction consistency for the previous data stream. However, selecting buffered samples randomly in the uniform distribution may not reflect proper industrial domain shifts. In contrast to previous methods of selecting samples for buffer randomly, we employ a novel sampling score based on the intuition that samples should be kept in buffer based on their potential prediction alteration after fine-tuning with new data. The potential was formulated using variational inference to ensure consistency in predictions across consecutive fine-tuning phases, but the derivation becomes intractable due to the ambiguity in predictions from future models. To address the intractability of this derivation, a meta-learning-based approach that predicts future model shifts based on past model updates was designed. Interestingly, after the derivation, our scoring method accounts for both category balance and representation variance within each category, which are important factors in industrial domains. The proposed continual learning method is validated with the actual industrial RT images of welding points from tubes, pipes and plates. We verified the different data streams, which are categorized over different sources of RT film scanner and over different defect information acquired along time. Our continual learning approach ensures that the detection model's performance preserves even after fine-tuning, without relying on all the original data. Compared to previous continual learning methods, our approach demonstrates state-of-the-art performance, validating its effectiveness in industrial domains and it may expand toward applicable domains which deal with object detection task.