



Survey paper

Continual learning in medical image analysis: A comprehensive review of recent advancements and future prospects

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ABSTRACT

Medical image analysis has witnessed remarkable advancements, even surpassing human-level performance in recent years, driven by the rapid development of advanced deep-learning algorithms. However, when the inference dataset slightly differs from what the model has seen during one-time training, the model performance is greatly compromised. The situation requires restarting the training process using both the old and the new data, which is computationally costly, does not align with the human learning process, and imposes storage constraints and privacy concerns. Alternatively, continual learning has emerged as a crucial approach for developing unified and sustainable deep models to deal with new classes, tasks, and the drifting nature of data in non-stationary environments for various application areas. Continual learning techniques enable models to adapt and accumulate knowledge over time, which is essential for maintaining performance on evolving datasets and novel tasks. Owing to its popularity and promising performance, it is an active and emerging research topic in the medical field and hence demands a survey and taxonomy to clarify the current research landscape of continual learning in medical image analysis. This systematic review paper provides a comprehensive overview of the state-of-the-art in continual learning techniques applied to medical image analysis. We present an extensive survey of existing research, covering topics including catastrophic forgetting, data drifts, stability, and plasticity requirements. Further, an in-depth discussion of key components of a continual learning framework, such as continual learning scenarios, techniques, evaluation schemes, and metrics, is provided. Continual learning techniques encompass various categories, including rehearsal, regularization, architectural, and hybrid strategies. We assess the popularity and applicability of continual learning categories in various medical sub-fields like radiology and histopathology. Our exploration considers unique challenges in the medical domain, including costly data annotation, temporal drift, and the crucial need for benchmarking datasets to ensure consistent model evaluation. The paper also addresses current challenges and looks ahead to potential future research directions.

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1. Introduction

In the evolving field of medical image analysis, the dynamic nature of healthcare data poses a critical challenge for the generalizability of the machine learning/deep learning models to new data/domains (Miotto et al., 2017; Zhou et al., 2021a). The data-driven approaches have challenges due to the limited availability and accessibility of sufficiently large and diverse medical data for training (Miotto et al., 2017; Guan and Liu, 2022; Zhou et al., 2021a; Chauhan and Goyal, 2020, 2021). Additionally, the source variability due to different scanner manufacturers, staining and imaging protocols, slice thickness, different patient cohorts, etc., makes the medical data heterogeneous. This introduces bias and discrepancies between the training and test datasets if they originate from different data sources, thus leading to performance degradation (Oliveira et al., 2023; Zhou et al., 2021a). In order to handle the model generalizability issues, domain adaptation methods become popular and aim to transfer knowledge from one domain to other unseen data sources or domains (Lai et al., 2023a,b; Guan and Liu, 2022; Wachinger et al., 2016; Becker et al., 2014; Feng et al., 2023). However, domain adaptation poses unique challenges due to the sensitive and complex nature of healthcare data (Azad et al., 2022). The most common associated issues are the limited availability of labeled medical data for training, heterogeneity in data sources contributing to significant domain shifts, clinical disparities and population variances, and inter-rater variabilities. Also, biases present in the source domain data can propagate to the target domain, so ensuring fair and unbiased predictions across diverse patient populations becomes a critical concern. Moreover, medical data encompasses various modalities, including imaging, electronic health records, and genomic data, making the task of adapting models to handle multimodal data and ensuring interoperability exceptionally complex. Further, the accessibility of source data may be limited to a short period of time or may be prohibited altogether due to strict privacy regulations in the medical domain (Thandiackal et al., 2024). Thus, domain adaptation

approaches that require simultaneous availability of source and target data may not be feasible.

Another related learning paradigm, transfer learning, has been widely adopted in the medical domain to address challenges related to limited data availability (Yu et al., 2022; Ghafoorian et al., 2017). It transfers knowledge gained from the source task to the target task to improve its learning or performance. Unlike domain adaptation, where only the data distribution changes, transfer learning covers changes in the feature space, label space, as well as in the data distribution of the source and target domain (Kouw and Loog, 2018; Zhou et al., 2022; Guan and Liu, 2022). In a small-scale medical disease classification dataset, it can be beneficial to include knowledge gained from a model trained on a large-scale labeled natural image dataset (ImageNet). The model performance on the medical disease dataset may be better as compared to training the same model solely on the medical disease dataset from scratch. However, at the same time the performance on the ImageNet dataset cannot be guaranteed by this model (which is also not intended in transfer learning). In transfer learning, the focus is on leveraging prior knowledge rather than retaining it, hence performance on the source data may be compromised. Generally, learning a new dataset with shifted distribution results in a sharp decrease in performance on the source dataset, also known as “catastrophic forgetting” of deep neural networks (McCloskey and Cohen, 1989; Goodfellow et al., 2013). A detailed description of catastrophic forgetting is provided in Section 2.2.

In the real world, sequential adaptation to more than one target domain, without necessitating the availability of source data can be desired. In this direction, Continual learning (CL) - continuous adaptation to new information, has emerged as an important dimension in enhancing the performance and reliability of medical image analysis systems. Unlike transfer learning, CL focuses on both the source domain and the target domain. A CL approach aims to retain knowledge from previously seen tasks while adapting to new tasks and avoiding catastrophic forgetting issues. CL models are employed for predictive analytics, especially in situations where clinical outcomes can be automatically

obtained and incorporated into the algorithm (Lee and Lee, 2020). This capability enhances the model's predictive power by learning from real-time patient data. CL methods can also be employed to utilize the multi-modality dataset for better interpretability and analysis. In recent years, an increasing number of CL methods have been explored and proposed in various subareas of computer vision tasks. Fig. 3 presents the paper distributions based on different aspects of CL and shows the growth in exploration in medical domain through the rising number of publications over the years. In this paper, we discuss the various aspects of CL, particularly considering its application and implications in the medical domain. Here, we aim to contribute to the ongoing discourse on adapting and improving machine learning models for sustained effectiveness in the dynamic healthcare landscape. By emphasizing CL, we recommend models that not only demonstrate robust performance initially but also possess the ability to evolve and improve over time. CL in medical image analysis represents a powerful approach to developing intelligent systems that can evolve, learn, and adapt to the complexities of healthcare, ultimately contributing to improved patient outcomes and enhanced clinical decision-making. We discuss the limitations and challenges of the existing methods and explore the methods/techniques that can be utilized for developing a robust algorithm. A thorough search of the existing body of literature highlights the uniqueness of our work as the first comprehensive survey of CL techniques applied to medical image analysis. This scholarly endeavor aims not only to contribute novel insights but also to establish a foundational reference for researchers, offering a roadmap that can guide future exploration and incite scholarly interest in the academic community. The primary contributions of our academic pursuit are elucidated below:

- Pioneering in its scope, this survey paper provides the first comprehensive exploration of CL applications in the field of medical image analysis. Our focus extends to delivering a thorough overview encompassing all pertinent papers and elucidating details regarding well-known methods in medical image analysis.
- We introduce a rigorous categorization of CL models within the academic community, presenting a systematic taxonomy that categorizes research based on different CL strategies. Our classification discerns between various CL techniques, such as rehearsal, regularization, architectural, and hybrid methods. Additionally, we contextualize these techniques within various medical sub-fields, offering a nuanced academic perspective.
- Beyond application-centric discussions, our exploration delves into the scholarly challenges and open issues surrounding CL in medical image analysis. By addressing academic intricacies, including data annotation costs, temporal drift, and the necessity for benchmarking datasets, we contribute to the scholarly discourse. Additionally, we identify emerging academic trends that give rise to open questions, shaping the trajectory of future academic research in CL applied to medical image analysis.

Motivation and uniqueness of this survey

Over the past few decades, CL approaches in computer vision tasks have seen substantial progress, leading to numerous survey papers exploring deep CL models for computer vision tasks (Qu et al., 2021; Wang et al., 2023b; De Lange et al., 2021; Mai et al., 2022). While some of these surveys focus on specific applications, such as classifications (De Lange et al., 2021; Mai et al., 2022) others take a more general approach to evaluation policies (Mundt et al., 2021) or concepts and practical perspectives (Wang et al., 2023b). Notably, none of these surveys specifically addresses the applications of CL techniques in medical image analysis, leaving a significant gap in the literature. We believe that insights from successful CL models in vision can be beneficial for the medical community, guiding the retrospective analysis of past and future research directions in CL (Verma et al., 2023; Lee and Lee, 2020). CL has proven its potential in developing unified and sustainable deep models capable of handling new classes, tasks,

Table 1

Abbreviations and their expansion. Green rows signify abbreviations related to CL (scenarios and techniques), cyan corresponds to imaging modalities and techniques, while orange is associated with evaluation metrics.

Acronym	Full name
CL	Continual Learning
CIS	Class Incremental Scenario
DIS	Domain Incremental Scenario
TIS	Task Incremental Scenario
IIS	Instance Incremental Scenario
EWC	Elastic Weight Consolidation
DWC	Distributed Weight Consolidation
MAS	Memory Aware Synapses
SI	Synaptic Intelligence
sMRI	structural Magnetic Resonance Imaging
CMR	Cardiac Magnetic Resonance
CT	Computed Tomography
VQA	Visual Question-Answering
H&E	Hematoxylin and Eosin
sEMG	Surface electromyography
WSI	Whole Slide Images
wCC	weighted Correlation
PCC	Pearson Correlation Coefficient
rMSE	root Mean Square Error
FLOPS	Floating Point Operations Per Second
SRC	Spearman's rank correlation coefficient
KRC	Kendall rank correlation coefficient
AUPRC	Area Under the Precision-Recall Curve
SSD	Symmetric Surface Distance
IoU	Intersection over Union
AUC	Area Under ROC Curve
MAE	Mean Absolute Error
MCR	Mean Class Recall
AP	Average Precision
DSC	Dice Similarity Coefficient
HD95	95% Hausdorff Distance
PROC	Free-response Receiver-Operating Characteristic
ROC	Receiver-Operating Characteristic
MSD	Mean Surface Distance
ASSD	Average Symmetric Surface Distance
BWT	Backward transfer
FWT	Forward transfer
TPR	True Positive Rate
SNR	Signal-to-Noise Ratio

and the evolving nature of data in non-stationary environments across various application areas. Our survey aims to bridge the gap by providing valuable insights that can assist medical researchers, including radiologists, in adopting up-to-date methodologies in their fields. In our survey, we analyze various sources of drifts in medical data, defining CL scenarios in medical images. We present a multi-perspective view of CL by categorizing techniques into rehearsal, regularization, architectural, and hybrid strategies-based methods. The discussion extends beyond applications, encompassing underlying working principles, challenges, and the imaging modality of the proposed methods. We emphasize how this additional information can aid researchers in consolidating literature across the spectrum. A concise overview of our paper is illustrated in Fig. 6.

Search strategy

To conduct a thorough literature search, we followed the same strategy presented in Azad et al., Azad et al. (2023b, 2023a) and utilized DBLP, Google Scholar, and Arxiv Sanity Preserver, employing custom search queries to retrieve scholarly publications related to our topic-CL. Our search query was (continual learning | medical | sequence of tasks) (segmentation | classification | medical | lifelong learning). These platforms allowed us to filter results into categories such as peer-reviewed journal papers, conference or workshop proceedings, non-peer-reviewed papers, and preprints. We filtered our search results through a two-step process:

Table 2
Data drift categorization.

Drift type	Detail with example
Covariate drift	It refers to situations when input distribution $p(x)$ differs and conditional distribution $p(y x)$ remains same between source and target data. <i>Example:</i> Change in WSI staining type induces covariate drift. The model trained on H&E stained breast cancer data may not perform well on the same tissue with CD8 staining.
Label drift	It refers to situations when output distribution $p(y)$ changes, but the conditional distribution $p(x y)$ remains same. <i>Example:</i> Inter-annotators difference may induce this kind of drift as some experts may be biased toward annotating a particular disease class. Thus, some classes may be undersampled or oversampled in target compared to the source data.
Concept drift	It refers to situations when input and output distribution remains same but the conditional relation $p(y X)$ differs between source and target data. <i>Example:</i> association of chest X-ray to COVID +ve class changed over time with new findings.

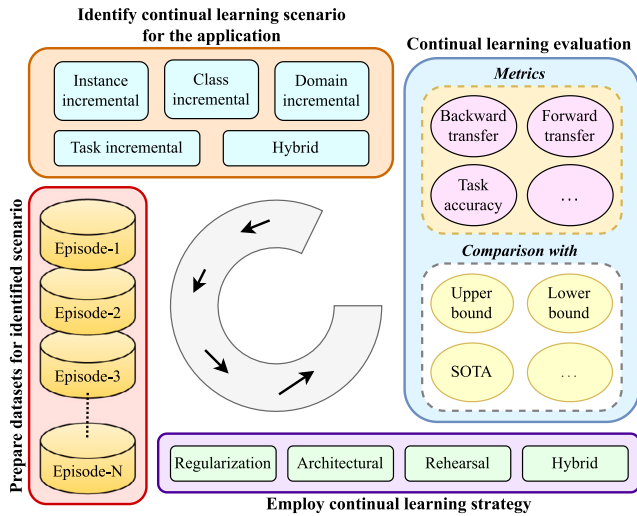


Fig. 1. A coarse level flowchart for designing a CL pipeline.

first by screening titles and abstracts, and then by reviewing the full text based on specific criteria as follows: 1. Relevance to Continual Learning: Focus on significant contributions to continual learning or related areas such as lifelong learning, incremental learning, and online learning. 2. Publication Venue: Preference for papers published in reputable journals and conferences known for high-quality research. 3. Novelty and Contribution: Inclusion of papers presenting novel research, methodologies, or applications. 4. Experimental Rigor: Papers must include comprehensive experiments and results validating their claims. 5. Theoretical Foundation: Preference for papers with a strong theoretical foundation, including formal definitions and analysis.

Paper organization

All the abbreviations used in this manuscript along with their expansion are tabulated in Table 1. A background about various sources of drift in medical data, the catastrophic forgetting issue, CL, a pipeline for CL framework, and CL applications is provided in Section 2. Then a thorough description of various kinds of continual learning scenarios explored in the medical domain is elaborated in Section 3. Further, we cover various categories of continual learning techniques and their applicability in the medical domain via Section 4. Section 5 provides details about the level of supervision required in different kinds of proposed frameworks. Section 6 provides comprehensive practical information such as the experimental setups, training process, and evaluation metrics for measuring the plasticity and stability of continual learning frameworks. Section 7 discusses the current challenges in the continual learning literature and future directions. Eventually, the last section provides the conclusion of the survey.

2. Background

2.1. Medical data drifts

In clinical practices, the data distribution evolves over time, reflecting the dynamic nature of the healthcare environment (Sahiner et al., 2023a; Lacson et al., 2022; Moreno-Torres et al., 2012). Inconsistencies in data collection procedures across different healthcare settings or institutions contribute to data drift. Also, the introduction of new medical imaging devices, diagnostic tools, and data acquisition techniques leads to a shift in the technological landscape (Derakhshani et al., 2022; Lacson et al., 2022). Moreover, the advancement in medical research and the discovery of new diseases/treatment methods raise the understanding of healthcare. This new knowledge can influence the characteristics of medical data that cause shifts in the underlying distribution (Lacson et al., 2022; Moreno-Torres et al., 2012). Also, data sources can have their dynamics and, therefore, are inherently non-constant. For instance, cardiac CT images are captured under time-varying factors such as breathing and heart rates. Non-homogeneous data is another challenge, as individual health differences among patients can vary over time due to factors like genetics, age, occupation, and lifestyle (Lacson et al., 2022; Sahiner et al., 2023b). Additionally, variations in sample preparation or pre-processing methods contribute to distinctions among imaging datasets. In digital histopathology, differences in staining policies across labs introduce undesired stain variances in whole-slide images (Nakagawa et al., 2023; Madabhushi and Lee, 2016). The imaging solution may also influence the final digital visualization throughout the entire learning process over time. Nonlinear augmentation of computed radiography occurs at various degrees due to the differing physical and chemical properties of contrast mediums from different brands. Variables like sensor signal-to-noise ratio (SNR), customized parameter settings in imaging software, and storage-friendly distortions can all impact the quality of the resultant image. For instance, in digital histopathology, billion-pixel whole slide images (WSI) at a fixed magnification have seen variations in storage size, ranging from megabytes to gigabytes per image over the years, consequently enhancing the dataset quality in terms of micron-per-pixel (MPP) for continual learning tasks (Nakagawa et al., 2023).

Data drifts can be broadly categorized as the covariate, label, and concept shift. We provide their explanation along with examples in Table 2. The medical data drifts can have significant implications for the performance and reliability of machine learning and deep learning models (Sahiner et al., 2023b). Traditional machine learning often relies heavily on static data and feature engineering, where human experts manually select the relevant features. In the case of data drift, these handcrafted features may become less informative, and the model may struggle to adapt to new patterns (Bayram et al., 2022). More specifically, for both machine learning and deep learning, this issue is particularly prevalent in dynamic and non-stationary environments, where the statistical properties of the data evolve. Understanding the sources of drift, such as inconsistencies in data collection and technological advancements, is crucial for developing robust models (Sahiner et al., 2023b). Proactive strategies, including regular model updates

and continuous monitoring, are essential to ensure that machine learning models remain effective and reliable in navigating the evolving healthcare landscape by addressing medical data drift and developing machine learning models that can adapt to the ever-changing nature of clinical data, ultimately enhancing patient care and outcomes.

2.2. Catastrophic forgetting

Throughout a lifetime, a human brain continuously acquires knowledge, and learning new concepts or tasks has no detrimental effect on previously learned ones. Instead, learning several closely related concepts even boosts the learning of all associated ones. In contrast, artificial neural networks, although inspired by the human brain, often suffer from 'catastrophic forgetting', a tendency to overwrite or forget the knowledge acquired in the past upon learning new concepts (McCloskey and Cohen, 1989; Ratcliff, 1990). This can be attributed to the fact that the model entirely optimizes for the given dataset. In other words, a model with optimized weights for a task **T1**, when trained on a new task **T2**, will freely optimize the existing weights to meet the objectives in task **T2**, which may now no longer be optimal for the previous task **T1**. This can be a significant challenge, especially in scenarios where an AI system is expected to learn and adapt to a stream of tasks or datasets over time. Catastrophic forgetting in neural networks is an interesting phenomenon that has attracted lots of attention in recent research (Goodfellow et al., 2013; Kumari et al., 2024a). Medical data often come from different sources with varying imaging protocols, equipment, and patient populations. For example, MRI scans from different hospitals may have distinct characteristics, leading to domain shifts that can cause a model to forget previously learned features when introduced to new data. Also, medical datasets are often limited in size and can be highly imbalanced, with some conditions being much more common than others. This imbalance can exacerbate catastrophic forgetting, as the model may overly specialize in newly introduced, more frequent classes at the expense of older, less frequent ones. Addressing catastrophic forgetting is crucial for the development of reliable and effective medical AI systems. By implementing strategies such as regularization, rehearsal, generative replay, dynamic architectures, and domain adaptation, researchers can enhance the robustness of models against forgetting, ensuring consistent and accurate performance in medical applications. This is essential for maintaining diagnostic consistency, adapting to new medical knowledge, and providing trustworthy clinical decision support.

2.3. Continual learning overview

A naive solution to deal with catastrophic forgetting can be re-training the model collectively on old and new data from scratch each time new data with drifted distribution or classes are encountered (Lee and Lee, 2020). This process mostly gives the desired classification or segmentation performance; however, it causes an intense burden on computing and storage requirements and, hence, is impractical for deployment. Additionally, the retraining process requires storing the past data and thus causes privacy violations, which can be a major bottleneck of such a strategy in healthcare applications.

Alternately, CL, also termed as 'continuously learning', 'incremental learning', 'sequential learning' or 'lifelong learning', has emerged as a promising solution in various fields to deal with the catastrophic forgetting issue (De Lange et al., 2021; Mai et al., 2022). It helps in efficiently leveraging existing knowledge and incorporating new information without the need for extensive retraining. The primary goal of CL is to develop techniques and strategies that allow a neural network to learn new tasks while retaining knowledge of previous tasks. In other words, it aims to enable the network to continually adapt to new information without completely erasing or degrading its performance on earlier tasks. Overall, CL helps to address the issue of catastrophic forgetting and minimizes the need for additional

resources to store historical data. CL offers a range of strategies and methods, such as regularization (constraining weight update to avoid forgetting learned concepts), rehearsal (partially using some form of old data to replay with current data), and architectural modifications (reserving or partitioning network for different tasks), to help neural networks remember and consolidate knowledge from past tasks. These strategies help prevent or reduce catastrophic forgetting and improve the generalization ability of the model.

2.4. Continual learning pipeline

The design of a CL pipeline is illustrated in Fig. 1 which provides an overview of the key components and stages involved in the construction of the CL pipeline. Given a problem statement, first, we need to identify which CL scenarios it falls under, i.e., whether there is a possibility of domain shifts in future data, inclusion of new classes, or the end application, i.e., the task itself may change. For example, if we want to develop a breast cancer classification model to be able to work on the H&E dataset from different centers then the datasets across centers may have drift and hence fall into the domain incremental scenario of CL. Detailed information about CL scenarios is provided in Section 3. Once we have identified the CL scenario, training, and testing, datasets need to be prepared to mimic a continual stream of datasets arriving one after another. The sequence of datasets is frequently referred to as tasks, experiences, or episodes in literature. We also use these terms interchangeably in this manuscript. For each episode, separate training and testing data is prepared; thus, for a given sequence of four datasets, the pipeline requires four train-test pairs to develop and evaluate a CL model. Once the datasets are ready, a CL strategy suitable to the application at hand is identified and deployed in any off-the-shelf deep classification or segmentation model. There are various CL strategies, some offering privacy-preserved learning, while some offer better performance but at the cost of more resources, storage, and privacy violations as they store some past data. Typically, the model is trained on the first training episode and evaluated on testing data from all the episodes. After this, the training shifts to the next episode, where the inclusion of partial training data from the previous episode is possible. Here, updating the model with new training data, the evaluation is again done on all the testing data, and the process repeats until the last episode. Application-specific performance metrics (e.g., accuracy, dice similarity coefficient, etc.) computed on testing data of each episode are observed and analyzed over the sequence. Then, we can compute various metrics on top of it to quantify forgetting and forward transfer. Lastly, the CL framework is evaluated against state-of-the-art works and non-CL methods offering upper and lower bounds of performance. Joint or cumulative training gives the highest average performance, whereas naively finetuning on the current episode gives the lowest performance (Kaustaban et al., 2022; Lenga et al., 2020).

2.5. Application of continual learning

CL has numerous applications across various domains due to its ability to mitigate catastrophic forgetting. The efficiency and robustness of CL in real-time scenarios derive from its ability to adapt, reduce computational overhead, and address the challenges of dynamic data. This makes it a valuable approach for applications where time constraints, adaptability, and efficiency are of great importance. In the medical domain, CL has been widely explored for various segmentation and classification applications (Fig. 2) and continuously exhibited its merits over static models as reflected by the increasing number of research contributions over the year (Fig. 3). CL can improve the diagnosis and decision-making ability in a resource-constrained environment. Further, it is beneficial in real-time monitoring of patients, telemedicine, and maintaining a dynamic knowledge base. This section presents the most prominent applications of CL in medical settings in terms of the number of publications.

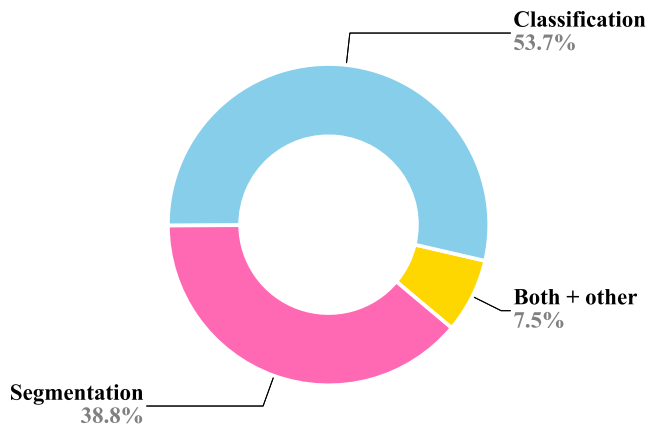


Fig. 2. Ratio of CL-based research for downstream applications.

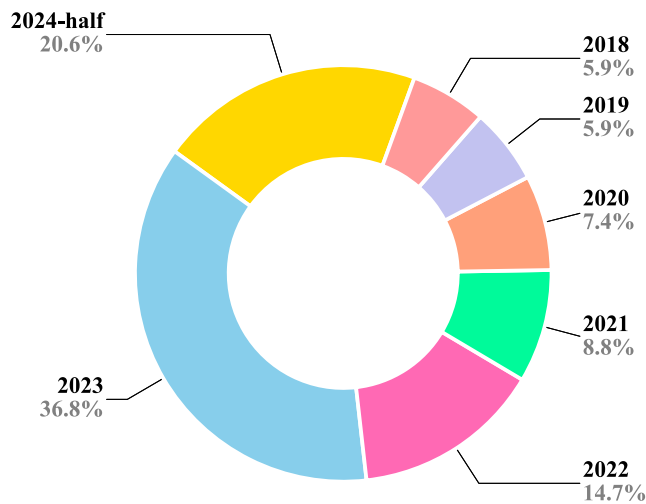


Fig. 3. CL-based research contributions over the years. Percentages represent the number of CL papers in the medical domain each year, showing the increasing trend and growing importance of CL research.

Radiology and imaging: Radiological imaging techniques are continually advancing, requiring models to adapt to new technologies and methodologies. For CT, research has investigated the impact of scanners and reconstruction parameters on both machine learning predictions and human annotations. The findings indicate that the variability introduced by different scanners has a detrimental effect on radiomics (Mackin et al., 2015; Prayer et al., 2021) and other imaging features. Therefore, it is imperative to take into account this scanner variability when developing machine learning models. CL facilitates the dynamic adjustment of models to evolving imaging techniques, ensuring accurate interpretations (Li and Hoiem, 2018; Zhang et al., 2023d). Tables 15 and 16 present the selected works for CL-based classification and segmentation in the medical domain.

Disease progression modeling: CL is crucial in tracking the progression of diseases such as Alzheimer's Disease (AD). Models must adapt to new patient data over time, incorporating the latest diagnostic criteria and treatment strategies (Li et al., 2020b). Recent work was proposed for modeling AD progression in a CL manner that respects the longitudinal data sets coming in sequence and ensures equal prediction accuracy for future visits (Zhang and Wang, 2019a).

Drug discovery: CL can accelerate drug discovery by continuously integrating newly discovered chemical compounds, pharmacological data, and clinical trial results to predict drug interactions and efficacy. A recent work presented a CL-based model called Multi-Scale Temporal Convolutional Networks-based AntiBacterial Peptide Prediction

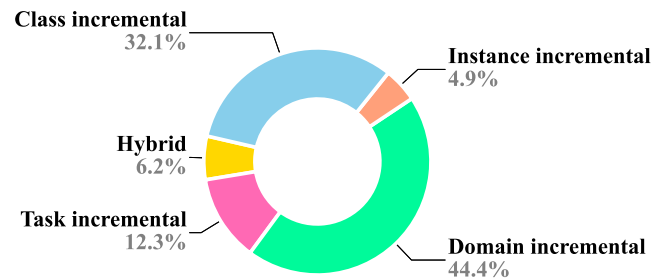


Fig. 4. Ratio of CL-based works for different incremental scenarios.

(MSTCN-ABPpred). This model is designed for the classification and discovery of antibacterial peptides (ABPs). While MSTCN-ABPpred can dynamically adapt and retrain based on predicted ABPs and non-ABPs within protein sequences, it does have limitations in terms of providing information about the identified ABPs' targets, haemotoxicity, cytotoxicity, and minimum inhibitory concentration (MIC) against various bacteria (Singh et al., 2023).

3. Continual learning scenarios

Depending upon what kind of change in the sequence of data is expected, the existing CL scenarios can be broadly categorized into five categories, viz., (a) instance-incremental, (b) class-incremental, (c) task-incremental, (d) domain-incremental, and (e) hybrid. Fig. 4 shows the percentages of the above-mentioned incremental CL scenarios exploited in recent years. The statistics reflect that domain-incremental is highly explored with a 44.4% ratio out of five major settings, followed by the class-incremental settings having 32.1% works and instance-incremental being the least challenging and rarely explored for different medical image analysis applications.

3.1. Instance incremental scenarios

Instance Incremental Scenario (IIS), also termed as data incremental scenario, involves the continuous learning process where the model keeps adapting to incoming data streams that come from the same data distribution. This scenario does not involve dealing with entirely new categories or significant changes in data patterns, making it generally the least challenging among all other CL scenarios. In the medical domain, especially digital pathology, a common practice is for expert pathologists to annotate a dataset in multiple stages or batches (Kaustaban et al., 2022). Each of these annotation batches can be thought of as representing samples from the same underlying data distribution, ensuring some consistency in the data source across different batches. Thus, IIS scenarios deal with the condition where the samples of a dataset are sequentially made available. Owing to its simplicity, this category is not very popular. Only a few classification applications are explored in this scenario, as mentioned in Table 3. For example, in the breast cancer classification application, Chen and Tang (2022) set up IIS on the BreakHis (Spanhol et al., 2015) dataset. More and more samples from each of the malignant and benign classes are added over the subsequent episodes. Ravishankar et al. (2019) try to exhibit a scenario for pneumothorax detection in a hospital where data arrives in an incremental fashion. They sequentially fed 2000 samples in 4 subsequent episodes from an X-ray dataset for Pneumothorax identification consisting of a total of 8000 samples. A label drift is also possible in real-world IIS settings. However, the majority of previous works deliberately curate a similar amount of samples for a particular class over episodes, and hence, label drift phenomena are not considered. One potential solution to produce the desired number of samples for classes affected by label-shift from past episodes would be to use a generator model such as GAN (Byun et al., 2023).

Table 3List of various **instance** incremental scenarios in literature.

Reference (year)	Application (# Episodes)	Description
Ravishankar et al. (2019)	Pneumothorax identification from X-ray images (2 Ep.)	4 batches each of 2K were created from a subset of ChestXRay (Wang et al., 2017)
Kaustaban et al. (2022)	Histopathology data-based tumor classification (4 Ep.)	Tasks were created in instance incremental fashion from colorectal cancer dataset CRC (Kather et al., 2019) having a total of 9 classes, (i.e., all 9 classes are present in each episode)
Wei et al. (2023)	Brain tumor segmentation (8 Ep.)	Starting from 160 samples, authors incrementally add 40 more samples after each training session from the LGG Segmentation dataset (Buda et al., 2019)
Bringas et al. (2024)	Alzheimer's disease stage identification using motion-sensor (2 Ep., 3 Ep., 4 Ep.)	3 experiments were designed with 2, 3, and 4 episodes having per-episode 374, 249, and 187 samples, respectively.

3.2. Class incremental scenarios

Class Incremental Scenario (CIS) refers to a situation where the aim is to adapt the model to accommodate novel classes from new data streams. Given that each batch of these unseen classes offers knowledge that largely differs from the previous batches, this scenario is anticipated to be the most challenging among continual learning scenarios. An instance of this challenge is incorporating new types of tissues into a tumor classification model or introducing novel cell types into a model designed for AI-assisted diagnosis in cell detection. In this scenario, there is only one incremental task that gets additions of new classes in subsequent episodes. Some works assume mutually exclusive classes, whereas some classes are overlapping.

Multi-class datasets with more than 5–6 classes are mainly considered to create a class incremental scenario. There can be an equal or variable number of classes across the episodes. Chen and Tang (2022) propose a breast cancer classification model where they iteratively include malignant and benign classes with one sub-class from each category. This scenario is very popular for segmentation applications where the model may be demanded to segment more and more classes over time. An exhaustive list of class incremental scenarios explored in literature is provided via Table 4. References, along with detailed segmentation or classification applications, are tabulated.

3.3. Task incremental scenarios

Task Incremental Scenario (TIS) comes into the picture when we have a multi-task problem and a single adaptive model is desired. Each task is considered an episode. Thus each episode has disjoint label space. However, there is ambiguity in the literature with task incremental scenarios as the other scenarios (class and domain) are frequently referred to as task incremental scenarios by different research communities. For example, Ravishankar et al. (2019) create the first episode having 2 chest X-ray views (2ch vs. PLAX) and then the next episode with 2 other views (4ch vs. PSAX) as a task incremental scenario, which can also be a class incremental scenario. Further, another example in this line can be found in the work by Baweja et al. (2018). Here, the authors create a task incremental scenario with 2 episodes for brain MRI segmentation application where the 1st episode was multi-class segmentation of cerebrospinal fluid, grey matter, and white matter, and the 2nd episode was the segmentation of white matter lesions. If we have multiple tasks that are very different, then it would certainly be the task incremental; however, if the tasks are more close then it is merely a design choice whether to treat them as class incremental or task incremental. Another work where Kaustaban et al. (2022) explore domain incremental scenario as organ shift for tumor classification problem where the first episode is a colon cancer dataset with nine classes (CRC dataset), and the next episode is a breast cancer dataset with 2 classes (PatchCam dataset). Similar is the case with Sadafi et al. (2023) where White Blood Cells (WBC) classification from 3 datasets, each having a different number of classes, is regarded as domain incremental, which can also be regarded as

task-incremental. Derakhshani et al. (2022) curate class incremental and task incremental scenarios from the same dataset taken from MedMNIST (Yang et al., 2023c) where a dataset is divided into non-overlapping classes leading to 4 episodes. If the model is evaluated only on the learned class in the specific episode, then they regard it as task incremental; otherwise, if evaluated on cumulative classes from all seen episodes, then class incremental scenario. Kaustaban et al. (2022) say that any of the scenarios among instance, class, and domain incremental can be treated as task incremental, provided that each incoming data stream (episode) is treated as a distinct task. For a comprehensive overview, we have tabulated all the works along with their claimed task incremental scenario in Table 5.

Further, it is essential to consistently provide prior information about which specific task (referred to as task identity, i.e., task ID) the test data pertains to, and predictions are made accordingly. However, if task IDs are not provided, then this category is termed as a task-free scenario which is a more challenging one.

3.4. Domain incremental scenarios

Domain Incremental Scenario (DIS) is the most popular and frequently observed category of CL scenarios for medical applications. Similar to IIS, here also, the task remains the same over time. However, in contrast to IIS, where data arrives from a single domain, here, the episodic data originates from a different domain or context. This scenario aligns with the idea of learning in a changing environment where the datasets from different domains (e.g., research sites, hospitals, imaging modality, image acquisition protocol, etc.) are incrementally encountered over time, which thus involve covariance shift-induced discrepancies in data.

In clinical applications, this might encompass changes in factors like the methods used for tissue processing and staining, the demographics of the patient population, or the types of scanning instruments employed, among other variables. Thus, continuous modifications in diagnostic techniques result in alterations in the appearance of medical images. Factors such as the brand of the scanning machine, the method used to create the images, radiation dosage, and specific settings in the scanning process, including the use of contrast agents, can all influence how the images look. These changes in image characteristics, which occur independently of the actual biological content being scanned lead to domain shifts.

Even if we have a single task and a fixed number of classes, these shifts can pose a challenge for the static deep model used in clinical settings because these shifts can quickly make existing models outdated and less effective. Here, a CL model aims to continuously update itself by incorporating new data streams that come from distributions that have shifted over time.

There have been plenty of attempts to develop CL models and evaluate different kinds of domain incremental scenarios. All the domain incremental scenarios are not equi-hard; some works consider a simpler level of domain shift, whereas some have a severe domain shift. To provide a comparative view, we tabulate all the domain incremental scenarios considered in literature through Table 6.

Table 4

List of various class incremental scenarios in literature.

Reference (year)	Application (# Episodes)	Description
Ozdemir et al. (2018)	MRI based humerus and scapula segmentation (2 Ep.)	Incrementally adding anatomical structure, private data
Ozdemir and Goksel (2019)	MRI based knee segmentation (2 Ep.)	SKI10 MICCAI Grand Challenge (Heimann et al., 2010)
Li et al. (2020b)	Dermoscopic images based skin disease classification (4-20 Ep.)	(a) CIS for Skin8 dataset having total 8 classes on which 2 classes per episode used, (b) CIS for Skin40 dataset from ISIC2019 (Tschandl et al., 2018) consists of 40 classes of skin disease images collected from the internet, here 2/5/10 classes per episode used in 3 experiments, (c) non-medical dataset CIFAR100 with 100 classes, here 5/10/20 classes per episode used in 3 experiments.
Liu et al. (2022)	Class incremental segmentation of abdomen organs (4 Ep.)	4 episodes were created for incremental segmentation of liver, spleen, pancreas, right kidney, and left kidney organs from CT datasets (Anon, a; Simpson et al., 2019), KiTS (Heller et al., 2019) + private
Derakhshani et al. (2022)	Disease classification (4 Ep.)	TissueMNIST, OrganaMNIST, PathMNIST, and BloodMNIST datasets from MedMNIST repository (Yang et al., 2023c) were used in 4 experiments, each with 4 episodes.
Akundi and Sivaswamy (2022)	Chest X-ray classification in CIS (5 Ep.)	5 classes from CheXpert dataset
Kaustaban et al. (2022)	Histopathology data based tumor classification (4 Ep.)	4 episodes were created in CIS from Colorectal cancer dataset CRC (Kather et al., 2019) having a total 9 classes
Chen and Tang (2022)	Histopathology data-based breast cancer classification (4 Ep.)	4 episodes created in CIS from BreakHis dataset
Zhang et al. (2023c)	(a) CT based abdomen, gastrointestinal, and other organ segmentation (7, 3, 4 classes in 3 Ep.), (b) abdomen segmentation to liver tumor segmentation task (13 classes, 1 class in 2 Ep.)	(a) Abdomen segmentation from JHH (Xia et al., 2022) (private) (b) 13 class abdomen segmentation dataset as BTCV (Landman et al., 2015) and liver tumor segmentation data as LiTS (Bilic et al., 2023)
Ji et al. (2023)	3D CT scan based whole-body organs segmentation (4 Ep. in 2 permutations of episodes)	TotalSegmentator (Wasserthal et al., 2023) (103 classes: various organs), 3 private datasets: ChestOrgan (31 classes: chest scans), HNOrgan (13 classes: head and neck scans), EsoOrgan (1 class: esophageal cancer)
Chee et al. (2023)	(a) Cancer classification (3,5 Ep.), (b) diabetic retinopathy classification (2 Ep.), (c) skin lesions classification (3,4 Ep.)	(a) Histopathology data based human colorectal cancer classification: CCH5000 (Kather et al., 2016) (total 8 classes, Exp=(4,1,1,1,1) classes, Exp=(4,2,2) classes), (b) diabetic retinopathy (DR) classification using retinal images: EyePACS (Anon, b) (total 5 classes: no DR, mild DR, moderate DR, severe DR and proliferative DR, Exp=(3,2) classes), (c) pigmented skin lesions classification: HAM10000 (Tschandl et al., 2018) (total 7 classes: Exp=(4,1,1,1) classes, Exp=(4,2,1) classes)
Zhang et al. (2023b)	Disease classification (4-10 Ep.)	(a) skin lesions classification with Skin8 dataset (International Skin Imaging Collaboration (ISIC) (Tschandl et al., 2018)) having 8 classes distributed over 4 episodes, (b) Path16, a pathology image collection from various public sources: total 16 classes distributed over 7 episodes, (c) CIFAR100: non-medical images, 100 classes distributed over 5-10 episodes
(Bai et al., 2023)	Surgical visual-question localized-answering	EndoVis18, EndoVis17, M2CAI
Sadafi et al. (2023)	Microscopic images based WBC classification (4 Ep.)	With 3 different datasets, 3 separate CIS experiments each having 4 episodes: (a) (3,3,3,4) classes from Matek-19 (Matek et al., 2019), (b) (3,3,3,4) classes from INT-20, and (c) (3,2,2,3) classes from Acevedo-20 (Acevedo et al., 2020)
Wang et al. (2023a)	(a) segmentation for endoscopy (2-3 Ep.), (b) surgical instrument segmentation (2 Ep.)	Incrementally adding segmentation structure from EDD2020 (Ali et al., 2021, 2020) dataset which includes 5 classes as Barrett's esophagus, cancer, high-grade dysplasia, polyp, and suspicious. Initially, 3-4 classes are in 1st episode, and then 2 or 1 classes are incrementally added in subsequent episodes. (b) EndoVis18 (Allan et al., 2020) and EndoVis17 (Allan et al., 2019) datasets as two episodes having some overlapping classes
Hua et al. (2023)	sEMG-based gesture classification (4 Ep.)	2 experiments were created, each with 4 episodes using Ninapro DB2 sEMG dataset for gesture recognition. The first experiment has (8, 11, 14, 17) gesture classes and the second experiment has (10, 20, 30, 40) gesture classless.
Huang et al. (2023)	Tumor subtype classification at WSI-level (4 Ep.)	Incrementally learning tumor classes using 4 datasets (NSCLC, BRCA, RCC, ESCA) from TCGA ^a project. Each dataset has 2 distinct tumor subtypes leading to a total 8 subtypes.
Xiao et al. (2023)	Skin disease classification (18 Ep.)	Incrementally learning 5 new skin disease classes in each episode
Li and Jha (2023)	Disease classification on physiological signals (2 Ep.)	3 separate experiments were designed, each with 2 episodes. (a) using CovidDeep (Hassantabar et al., 2021), 1st episode has healthy and symptomatic patients and 2nd episode only asymptomatic patients, (b) using DiabDeep (Yin et al., 2019) dataset: 1st episode has healthy and Type-I diabetic patients and 2nd episode only Type-II diabetic patients, and (c) using MHDeep (Hassantabar et al., 2022) dataset: 1st episode has participants with healthy condition and major depressive disorder and 2nd episode has bipolar depressive disorder patients.

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3.5. Simulated or hybrid settings

It may not always be the case that the model observes a particular kind of incremental scenario, such as a domain incremental condition. The CL model developed for handling domain incremental conditions

may not perform well for a class incremental condition. Thus, there are attempts to evaluate the same model on different CL scenarios; however, a separate evaluation is followed for each kind of incremental CL scenario. In contrast, having a set of episodes with a mix of CL scenarios is close to real-life conditions. Thus it becomes important

Table 4 (continued).

Reference (year)	Application (# Episodes)	Description
Sun et al. (2023c)	Multi-class classification on time-series signals (5 Ep., 10 Ep., 5 Ep., 4 Ep.)	4 separate experiments were designed as follows: (a) using Mit-BIH dataset (Goldberger et al., 2000) 4 episodes were created where 1st episode has 4 classes and the 4 new classes are added one by one in the next 4 episodes. (b) using FaceAll dataset (Dau et al., 2019), 10 episodes were created where 1st episode has 5 classes and the next 9 episodes introduce 9 new classes, one by one. (c) using Wave dataset (Dau et al., 2019) a total of 5 episodes were created where 1st episode has 12 classes and the next 4 classes introduce new 12 classes, 3 classes each. (d) using Mit-BIH Long-Term ECG dataset (Goldberger et al., 2000) 4 episodes were created where 3 classes were in 1st episode and the next 3 episodes contained 3 new classes, 1 class in each.
Yang et al. (2023a)	Skin disease classification on dermoscopic and clinical images: (4-20 Ep.)	2 datasets were used separately as follows: (a) Skin7 (Codella et al., 2018) containing a total of 7 classes is used in CIS where 1 and 2 classes are incrementally added leading to 6 and 4 episodes, respectively. (b) Skin40 dataset (Sun et al., 2016) containing a total of 40 classes is used in CIS where 2,5, and 10 classes are incrementally added leading to 20, 8, and 4 episodes, respectively.
Verma et al. (2023)	Disease classification on (a) fundus (3 Ep.), (b) pathology images: (3 Ep.)	(a) OCT dataset (Kermary et al., 2018) with total 4 classes used to create 3 episodes: episode-1 has two classes (Normal and Choroidal Neovascularization), episode-2 has 1 class (Diabetic Macular Edema) and episode-3 contains 1 class (Drusen). (b) PathMNIST dataset (Yang et al., 2023c) from the MedMNIST repository offers 9 classes for colon pathology. It is used to create 3 episodes with 3 classes each.
Ceccon et al. (2024a)	Chest X-ray based disease classification (5 Ep.)	2 datasets (ChestX-ray14 (Wang et al., 2017) with 14 classes and CheXpert (Irvin et al., 2019) with 12 classes) used separately to create two experiments, each with 5 episodes.
Bayasi et al. (2024b)	(a) Skin lesion classification (2-3 Ep.), (b) blood cell classification (4 Ep.), (c) colon tissue classification (4 Ep.)	(a) HAM10000 (Tschandl et al., 2018), Dermofit (Ballerini et al., 2013), and Derm7pt (Kawahara et al., 2018) datasets with total 7, 7, and 6 classes used to create 3, 3, and 2 episodes each with 2-3 non-overlapping skin disease classes, respectively, (b) PBS-HCB (Acevedo et al., 2020) dataset with a total of 8 classes used to create 4 episodes each with 2 non-overlapping blood cell classes, (c) NCT-CRC-HE (Kather et al., 2019) dataset with a total of 9 classes used to create 4 episodes each with 2-3 non-overlapping colon tissue classes.
Qazi et al. (2024)	(a) Disease classification in histopathology images: (7 Ep.), (b) Skin lesion classification: (4 Ep.)	(a) Using Path16 dataset 7 episodes were created as different sources of dataset with different classes from histopathology, (b) using skin8 dataset, a total of 4 episodes were created by adding 2 new classes per episode.
Zhu et al. (2024a)	Histopathology WSI retrieval: (4 Ep.)	Authors curate a sequence of 4 WSI datasets (NSCLC, RCC, BRCA and GAST) from TCGA. Each episode introduces a new dataset with 2 new classes of cancer, showing a CIS setting.

^a <https://www.cancer.gov/ccg/research/genome-sequencing/tcga>

Table 5

List of various task incremental scenarios in literature.

Reference (year)	Application (# Episodes)	Description
Baweja et al. (2018)	MRI-based normal brain structures segmentation (2 Ep.)	UK Biobank (Miller et al., 2016) dataset used to create two tasks: 1st) segmentation of cerebrospinal fluid, grey matter, white matter and 2nd) segmentation of white matter lesions.
Ravishankar et al. (2019)	Chest X-ray view classification (2 Ep.)	Shift from task (4ch vs. PLAX) to task (2ch vs. PSAX)
Zhang and Wang (2019b)	Longitudinal MRI-based Alzheimer's disease progression modeling (7 Ep.)	Tasks are MR images belonging to different time points
Kaustaban et al. (2022)	Histopathology data-based tumor classification (4 Ep.)	4 episodes were created in TIS from Colorectal cancer dataset CRC (Kather et al., 2019) having a total of 9 classes
Derakhshani et al. (2022)	Disease classification (4 Ep.)	4 episodes were created from each of the datasets in TissueMNIST, OrganaMNIST, PathMNIST, BloodMNIST (MedMNIST repository (Yang et al., 2023c))
Bera et al. (2023)	MRI-based binary segmentation (3 Ep.)	3 episodes were curated as binary segmentation application using MRI data on 3 organs (prostate, spleen, hippocampus): Promise12 (Litjens et al., 2014) (prostate) → MSD (Anon, c) (spleen) → Drayd (Denovellis et al., 2021) (hippocampus)
Wu et al. (2024)	Image super-resolution (4 Ep.)	First 3 episodes are curated from IXI (IXI) dataset referring to (PD, T1, and T2) weighted brain MRI, and the last episode refers to chest X-ray from Chest X-ray (Wang et al., 2017) dataset.
Li and Jha (2023)	Disease classification on physiological signals (2-3 Ep.)	A task incremental scenario with 2-3 different disease classification tasks were created using 2-3 datasets (CovidDeep (Hassantabar et al., 2021), DiabDeep (Yin et al., 2019), and MHDeep (Hassantabar et al., 2022))
Verma et al. (2024)	Disease classification on (a) Fundus (2 Ep.), (b) pathology images (3 Ep.)	(a) OCT (Kermary et al., 2018) with total 4 classes used to create 2 episodes, each having 2 classes (b) PathMNIST (Yang et al., 2023c) from the MedMNIST repository offers 9 classes for colon pathology. It is used to create 3 episodes, each with 3 classes.
Ye et al. (2024)	Multi-modality representation learning (5 Ep.)	5 different medical data modalities including medical report, MRI, X-ray, CT, and histopathology data were learned in 5 episodes for SSL-based representation learning

to also test the performance in hybrid settings. Table 7 provides a comprehensive overview of works that designed hybrid incremental scenarios.

An attempt in direction is made by Sadafi et al. (2023) where other than pure domain incremental and class incremental, a hybrid incremental scenario is also considered. The authors create a sequence

of episodes with both class and domain-incremental cases on multi-site WBC classification datasets. They create a long sequence of episodes with a total of 12 episodes. First, they set up a class incremental scenario within the Matek-19 (Matek et al., 2019) dataset by adding 3–4 classes in each subsequent episode up to a total of 4 episodes. After this a new domain, i.e., the INT-20 dataset was considered in the same

Table 6

List of various domain shift scenarios in literature.

Reference (year)	Shift source (# Episodes)	Description
McClure et al. (2018)	Cross-site (4 Ep.)	sMRI based Axial and sagittal brain segmentation: datasets from 4 sites: HCP (Van Essen et al., 2013), NKI (Nooner et al., 2012), Buckner (Biswal et al., 2010), WU120 (Power et al., 2017) in different order
Karani et al. (2018)	Cross-scanners, hospitals, or acquisition protocols (4 Ep.)	MR brain segmentation on various combinations using 5 datasets from different sources: Human Connectome Project (Van Essen et al., 2013), Alzheimer's Disease Neuroimaging Initiative (ADNT), Autism Brain Imaging Data Exchange (Di Martino et al., 2014) and Information eXtraction from Images (IXI)
van Garderen et al. (2019)	Low vs. high-grade (2 Ep.)	MR data based glioma segmentation: 2018 BraTS Challenge (low and high-grade), an in-house dataset with non-enhancing low-grade
Venkataaramani et al. (2019)	Varying in disease type, intensity patterns (2) & contrast	X-ray lung segmentation: Montgomery (Jaeger et al., 2014) as source, JSRT (Shiraishi et al., 2000) and Pneumoconiosis (private) as two target domains
Ravishankar et al. (2019)	Inter-subject variability (2 Ep.)	(a) Chest X-ray view classification (4ch vs. PLAX) from adult to pediatric as two domains (b) chest X-ray view classification (2ch vs. PSAX) from adult to pediatric as two domains
Lenga et al. (2020)	Cross-sites (2 Ep.)	Chest X-ray classification on datasets from 2 sources: ChestX-ray14 dataset from NIH Clinical Center and MIMIC-CXR dataset from the Beth Israel Deaconess Medical Center
Özgün et al. (2020)	Different age ranges, MRI field strengths & presence of pathologies or motion artifacts (4 Ep.)	Brain MRI segmentation datasets: 4 Ep. were created from 3 datasets: CANDI (Kennedy et al., 2012) (1 Ep.), ADNI (Jack Jr. et al., 2008) (1 Ep.), and MALC (Asman and Landman, 2013) (2 Ep. based on age)
Hofmanninger et al. (2020a)	Different scanner parameters and target-shift (3 Ep.)	Chest CT synthetic classification task: the second episode have change in scanner parameter as compared to first episode (Hofmanninger et al., 2020b), then target shift is introduced intentionally in the third episode by imprinting a synthetic target structure in the form of a cat on random locations, rotations and varying scale in 50% of the samples.
Morgado et al. (2021)	Appearance and body-parts (2 Ep.)	Dermatological imaging modality classification (full-body, anatomic, macroscopic, and dermoscopic classes): For each of the classes, author considered disjoint images in the two episodes, for example, in the second episode, legs and arms images were considered for full-body class, images containing hands or feet only considered for anatomic, images containing face region for macroscopic class, and pink colored images for dermoscopic class.
Srivastava et al. (2021)	Cross-sites (3 Ep.)	Chest X-ray classification: NIH Chest-X-rays14, PadChest, and CheXpert
Mommel et al. (2021)	Multi-scanner (2 Ep.)	MRI-based Hippocampal Segmentation: 3 datasets as 2018 Medical Segmentation Decathlon challenge (Simpson et al.), Scientific Data (Kulaga-Yoskovitz et al., 2015), and Alzheimer's Disease Neuroimaging Initiative (Boccardi et al., 2015): 2 datasets together in 1st episode and then 3rd dataset in 2nd episode, different such combinations were experimented
Perkonig et al. (2021)	Multi-scanners (3 Ep.)	Brain age estimation: IXI(IXI) (Philips Gyroscan Intera 1.5T, Philips Intera 3.0T scanner), OASIS3 (LaMontagne et al., 2019) (Siemens TrioTim 3.0T scanner)
Bayasi et al. (2021)	Multi-site (6 Ep.)	Skin lesion image classification: HAM10000 (Tschandl et al., 2018), Dermofit (Ballerini et al., 2013), Derm7pt (Kawahara et al., 2018), MSK (Codella et al., 2018), PH2 (Mendonça et al., 2013), UDA (Codella et al., 2018)
Zhang et al. (2021)	Cross-sites (6 Ep.), (4 Ep.)	(a) Prostate segmentation: MRI datasets across 6 sites: RUNMC (Bloch et al., 2015), BMC (Bloch et al., 2015), HCRUDB (Lemaître et al., 2015), UCL (Litjens et al., 2014), BIDMC (Litjens et al., 2014), HK (Litjens et al., 2014), (b) optic cup and disc segmentation: public multi-site fundus image datasets from 4 sources (Sivaswamy et al., 2015; Fumero et al., 2011; Orlando et al., 2020)
Perkonig et al. (2022)	Multi-scanner (4 Ep.)	(a) CMR based Cardiac segmentation (4 Ep.): Cardiac (Campello et al., 2021), (b) CT based Lung nodule detection (4 Ep.): LIDC (Setio et al., 2017), + LND challenge (Pedrosa et al., 2019), (c) MRI based Brain Age Estimation segmentation (4 Ep.): IXI(IXI) + OASIS-3 (LaMontagne et al., 2019)
Derakhshani et al. (2022)	Across organs or modality (4 Ep.)	Disease classification: 4 episodes using 4 datasets ordered as: BloodMNIST, OrganaMNIST, PathMNIST, TissueMNIST (MedMNIST repository)
Karthik et al. (2022)	Cross-center (8 Ep.)	Sclerosis lesions segmentation from brain MRI datasets described in Kerbrat et al. (Kerbrat et al., 2020)
González et al. (2022)	(a) Cross-domain (5 Ep.), (b) manual image contrast change (5 Ep.)	MRI hippocampus segmentation: (a) HarP (Boccardi et al., 2015), Dryad (Kulaga-Yoskovitz et al., 2015), Decathlon (Simpson et al., 2019), (b) data transformation applied using TorchIO library on Decathlon (Simpson et al., 2019) as intensity rescaling, affine transformations, rotation, translation
Ranem et al. (2022)	Cross-site (3 Ep.)	MRI based binary hippocampus segmentation: Decathlon (Antonelli et al., 2022), Drayd (Denovellis et al., 2021), HarP (Boccardi et al., 2015)
Kaustaban et al. (2022)	(a) Multi-organ (2 Ep.), (b) scanning protocol (5 Ep.)	(a) Tumor classification: CRC (a colon cancer dataset with 9 classes), PatchCam (a breast cancer dataset with 2 classes), (b) Tumor classification: 5 domain shift scenarios were simulated by changing H&E composition in CRC dataset
Shu et al. (2022)	(a) Imaging protocol (2 Ep.), (b) multi-source (3 Ep.)	(a) Low and high-quality fundus images (retinal images) from EyeQ dataset as domain shift condition (Fu et al., 2019), (b) fundus disease classification (AMD, DR, glaucoma, myopia, and normal classes) across 3 datasets: ODIR (ODIR), R&R (RIADD (RIADD) + REFUGE (REFUGE)), and iSee (Fang et al., 2020)
Li et al. (2022)	Multi-scanner vendors (4 Ep.)	CMR based Cardiac segmentation of left ventricle, right ventricle, and left ventricle myocardium: 4 episodes as 4 scanner vendors (Siemens, Philips, General Electric, Cannon) from M&Ms (Campello et al., 2021) dataset

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Table 6 (continued).

Reference (year)	Shift source (# Episodes)	Description
Sadafi et al. (2023)	Cross-sites (3 Ep.)	WBC classification across 3 datasets: Matek-19 (Matek et al., 2019), INT-20, and Acevedo-20 (Acevedo et al., 2020)
Bera et al. (2023)	(a) Cross-center (4 Ep.), (b) cross-center (2 Ep.)	(a) Binary prostate segmentation: Prostate158 (Adams et al., 2022) → NCI-ISBI (Anon, c) → Promise12 (Litjens et al., 2014) → Decathlon (Antonelli et al., 2022), (b) binary hippocampus segmentation: Drayd (Denovellis et al., 2021) → HarP (Boccardi et al., 2015)
Zhu et al. (2023)	(a) Cross-site (6 Ep.), (b) cross-site & cross-modality (2 Ep.), (c) same-site & cross-modality (2 Ep.)	(a) Binary prostate segmentation from T2-weighted MRI scans collected from 6 sites (12–30 scans/site) (Liu et al., 2020a; Bloch et al., 2015; Lemaître et al., 2015), (b) multi-class (liver, left and right kidneys, and spleen) abdominal segmentation between 30 CT and 20 MRI T2-SPiR scans, (c) muscle segmentation of 13 lower-leg muscles and bones between 30 MRI T1 and 30 mDixon scans
Bándi et al. (2023)	Cross-organ (3 Ep.)	Histopathology data based cancer detection from breast (CAMELYON16, CAMELYON17), colon (private), and head-neck (private) datasets
Byun et al. (2023)	Various demographics, collection periods, camera types, and image quality (2–3 Ep.)	(a) Diabetic retinopathy severity classification across 2 datasets (Messidor-2, APTOS), (b) dermatology skin lesion detection across 3 datasets (BCN2000, PAD-UEFS-20, HAM10000)
Sun et al. (2023a)	Data distribution shifts in time series vital signals (10 time-steps.)	Mortality prediction (COVID-19 (Yan et al., 2020) datasets), (b) Sepsis situation identification (SEPSIS (Seymour et al., 2017) dataset)
Li and Jha (2023)	Distributional-drift (2 Ep.)	Disease classification on physiological signals: for each of the 3 datasets (CovidDeep(Hassantabar et al., 2021), DiabDeep(Yin et al., 2019), and MHDDeep(Hassantabar et al., 2022)), 2 episodes were curated by splitting patient into 2 groups.
Chen et al. (2023)	Multi-site, multi-vendor (3 Ep., 3 Ep., 6 Ep.)	3 separate applications including (a) Optic disc, (b) cardiac, (c) prostate segmentation were considered in domain shift condition
Li et al. (2024)	Multi-vendor (5 Ep.)	MR Cardiac segmentation (LV, RV, MYO) with 2 datasets (ACDC and M&M). Episode-1 is from ACDC dataset which is collected from Siemens scanners and the next 4 episodes are from M&M dataset which is collected from 4 vendors (Siemens, Philips, General Electric, and Cannon).
Kim et al. (2024)	Multi-site (4 Ep.)	Arrhythmia detection on ECG datasets: 4 datasets ((Zheng et al., 2020), (Wagner et al., 2020), (Alday et al., 2020), (Liu et al., 2018)) used as 4 episodes
Aslam et al. (2024)	Data distribution shifts in time series vital signals (10 contexts with significant change in mean and standard deviation)	Disease outbreak detection via time series signal: 3 datasets (Mpox (Mathieu et al., 2022), Influenza (Anon, d), Measles (Anon, e)) were used separately to curate 10 episodes.
Bayasi et al. (2024b)	Multi-source (4 Ep.)	Skin lesion classification: 4 publicly available skin disease classification datasets (HAM10000 (Tschandl et al., 2018), Dermofit (Ballerini et al., 2013), Derm7pt (Kawahara et al., 2018), MSK (Codella et al., 2018)) were used as 4 episodes, all with same 4 classes of skin disease
Zhu et al. (2024b)	Multi-acquisition, multi-equipment	(a) Prostate segmentation (6 Ep.), (b) Cardiac segmentation (3 Ep.)
Thandiackal et al. (2024)	Multi-source (3 Ep.)	Histopathology tissue classification: 3 different datasets (K-19 (Kather et al., 2016), K-16 (Kather et al., 2019), CRC-TP (Javed et al., 2020)) are considered as 3 episodes which contain 7 medically relevant patch classes from H&E stained WSIs of colorectal biopsies

Table 7

List of various hybrid CL scenarios in literature.

Reference (year)	Application (# Episodes)	Description
Yang et al. (2023b)	MedMNIST (Yang et al., 2023c) based disease classification (4 Ep.)	CIS+DIS: 3 datasets (PathMNIST, DermaMNIST, and OrganAMNIST) as source domain and then 3 more datasets (RetinaMNIST, BreastMNIST, BloodMNIST) as domain shift but classes are added in the class incremental fashion with 1 class at a time
Liu et al. (2023a)	Brain tumor segmentation (3 Ep.)	CIS with domain shift conditions: incrementally learn tumor core (BraTS2013 (Menze et al., 2014) dataset), the enhancing tumor (TCIA (Clark et al., 2013) dataset), and edema (CBICA (Bakas et al., 2018) dataset) structures via three datasets, each following different data distributions
Sadafi et al. (2023)	WBC classification (3 Ep.)	DIS (multi-site) + CIS using 3 WBC classification datasets having different number of classes: CIS on Matek-19 (Matek et al., 2019) then shift to INT-20 dataset and use it in CIS manner then shift to Acevedo-20 (Acevedo et al., 2020) dataset and use in CIS manner
Ceccon et al. (2024b)	Chest X-ray based disease classification (7 Ep.)	Authors curate a novel scenario termed NIC by interleaving new classes and new instances (from a new dataset as a new domain) in a sequence. The first episode contains a fixed set of classes from ChestX-ray14 (Wang et al., 2017) dataset and then the same classes from CheXpert (Irvin et al., 2019) dataset were considered as second episode. Then some new disjoint classes from ChestX-ray14 were considered in the third and fourth episodes. Thus, authors interleave between new classes and new domains to curate a hybrid scenario containing a total of 7 episodes.
Bayasi et al. (2024b)	Skin lesion classification (5 Ep.)	CIS+DIS: 5 skin lesion classification datasets (HAM10000 (Tschandl et al., 2018), Dermofit (Ballerini et al., 2013), Derm7pt (Kawahara et al., 2018), MSK (Codella et al., 2018), UDA (Codella et al., 2018), BCN (Combalia et al., 2019), PH2 (Mendonça et al., 2013)) with different number of classes (overlapping) were sequentially arranged as 5 episodes which exhibit incremental class and domain simultaneously.

fashion, contributing 4 more episodes. Finally, a third domain i.e., a new dataset Acevedo-20 (Acevedo et al., 2020) was introduced with 4 episodes in class incremental fashion.

Compared to the natural image domain, novel class appearance along with domain shifts is more frequent in medical applications owing to inherent heterogeneity in staining agents, protocols, imaging

Table 8

List of various rehearsal based works in literature.

Reference (year)	Application & CL scenario	CL technique
Hofmanninger et al. (2020a)	Chest CT classification: DIS (3 Ep.)	Experience replay with a dynamic memory size where samples are ranked by computing Gram matrix on the last activation maps
Srivastava et al. (2021)	Chest X-ray classification: DIS(3 Ep.)	Latent replay
Perkonigg et al. (2021)	Brain age estimation: DIS (3 Ep.)	Experience replay
Perkonigg et al. (2022)	3 separate experiments for 3 applications: (a) cardiac segmentation: DIS (4 Ep.), (b) lung nodule detection: DIS (4 Ep.), and (c) brain age estimation: DIS (4 Ep.)	Experience replay
Karthik et al. (2022)	MRI data for brain sclerosis lesions segmentation: DIS (8 Ep.)	Random samples from each episode kept for experience replay
Li et al. (2022)	CMR based Cardiac segmentation across 4 scanners: DIS (4 Ep.)	Generative replay: style-oriented replay
Bera et al. (2023)	(a) Binary segmentation of prostate, spleen, and hippocampus: TIS, (b) binary hippocampus segmentation across 2 datasets: DIS, (c) binary prostate segmentation across 4 datasets: DIS	Experience replay based rehearsal strategy: store max K exemplars (half of the exemplars based on fraction of positive class content inside the image and other half based on gradient variation)
Wang et al. (2023a)	(a) Segmentation for endoscopy: CIS (2-3 Ep.) (b) surgical instrument segmentation (2 Ep.)	Generative replay
Byun et al. (2023)	(a) Diabetic retinopathy severity classification: DIS (2 Ep.), (b) dermoscopy skin lesion detection: DIS (3 Ep.)	Generative replay: The generator model is a conditional text-to-image diffusion model that is updated with current episode data and then used to generate labeled data for the current episode and stored in the buffer. Current episode data along with labeled data for each episode kept in the buffer, is utilized for fine-tuning the classifier.
Huang et al. (2023)	Tumor subtype classification at WSI-level: CIS (4 Ep.)	Experience replay
Sun et al. (2023a)	Disease classification in time-series signals: DIS (10 time-steps)	Experience replay (adaptive importance based replay)
Wei et al. (2023)	Brain tumor segmentation: IIS (8 Ep.)	Experience replay
Xiao et al. (2023)	Skin disease classification with dermoscopic and clinical images: CIS (18 Ep.)	Rehearsal (Memory buffer optimization: extension of GEM approach)
Li and Jha (2023)	Disease classification on physiological signals: DIS (2 Ep.), CIS (2 Ep.), TIS (2-3 Ep.)	(a) Experience replay: training loss based sample selection for the buffer, (b) generative replay: parametric (GMM) or non-parametric (KDE) models as a generator for past episodes.
Thandiackal et al. (2024)	Histopathology colorectal tissue classification: DIS (3 Ep.)	GAN-based generative replay
Bringas et al. (2024)	Alzheimer's disease stage identification using motion-sensor: IIS (2 Ep., 3 Ep., 4 Ep.)	Rehearsal (A-GEM)
Zhu et al. (2024a)	Histopathology WSI retrieval: CIS (4 Ep.)	Rehearsal (experience replay: memory bank with reservoir sampling)

techniques, vendors, etc. Therefore, there has been recent interest and development of a novel CL scenario that consider new classes as well as new domains/instances, also termed as 'New Instances and New Classes' (NIC) scenario (Ceccon et al., 2024b). The NIC scenario is particularly relevant for medical image analysis as it addresses the simultaneous occurrence of new types of medical conditions (new classes) and new patient data (new instances), which is common in clinical practice. This scenario emphasizes the need for CL methods that effectively handle class and domain incremental learning. In contrast to traditional class-incremental settings, which often do not account for data shift, Liu et al. (2023a) propose a method for brain tumor segmentation that incrementally adds structures under varying domain shift conditions, such as distinct sites, scanners, or MRI modalities. This approach addresses class-incremental learning by incorporating domain-specific variations. Bayasi et al. (2024b) tackle a hybrid continual learning (CL) scenario using five skin lesion datasets from different sources and domains, each containing overlapping and varying numbers of classes. By treating these five datasets as five sequential episodes, their approach exemplifies the integration of both class-incremental and domain-incremental challenges. Similarly, Ceccon et al. (2024b) addresses a hybrid CL scenario in the context of chest X-ray-based disease classification. They interleave disease classes and domains by utilizing datasets from two hospitals, each containing 18 classes, to curate a total of seven episodes. Each

episode introduces either new disease classes or a new domain, thus combining class-incremental and domain-incremental learning within their methodology. Medical applications frequently encounter novel classes and domain shifts due to the diversity in staining agents, imaging protocols, and vendor-specific techniques. This has led to the development of new CL scenarios or hybrid learning scenarios.

Further, there are some attempts to curate shifts in datasets and various incremental scenarios instead of collecting real datasets reflecting the situation. For example, Kaustaban et al. (2022) simulated domain shift in H&E stain exhibiting distinct appearance caused by different staining protocols. This dataset is designed to simulate real-world scenarios, where data shifts occur due to differences in scanners, stainers, reagents, and other factors. They considered 9 classes from CRC (Kather et al., 2019) which is a H&E stain-based colorectal cancer classification dataset. Each class is divided into 5 disjoint sets for 5 episodes. The first set, regarded as Domain1 is without any alteration and the next 4 sets for each class undergo various changes to create domain shift. A short description of 4 domain shifts is as follows: **Domain 2** (increased stain intensity, simulating, for example, concentration increase of the eosin and/or hematoxylin solutions, each with a different extent of change). **Domain 3** (decreased eosin stain intensity, simulating, for example, slides prepared from many years ago with fading stain). **Domain 4** (change of hue, simulating, for example, change of reagent manufacturer, scanner or stainer) **Domain**

Table 9

List of various regularization based works in literature.

Reference (year)	Application & CL scenario	CL technique
Baweja et al. (2018)	MRI-based normal brain structures segmentation: TIS (2 Ep.)	EWC
McClure et al. (2018)	Axial and sagittal brain segmentation: DIS (4 Ep.)	Distributed Weight Consolidation (DWC)
Zhang and Wang (2019b)	Longitudinal MRI-based Alzheimer's disease progression modeling: TIS (7 Ep.)	EWC
van Garderen et al. (2019)	MR data-based glioma segmentation: DIS (2 Ep.)	EWC
Özgün et al. (2020)	Brain MRI segmentation: DIS (4 Ep.)	Learning rate regularization built over memory aware synapses technique
Chen and Tang (2022)	Histopathology-based breast cancer classification: CIS (4 Ep.)	Regularization: EWC
Zhang et al. (2023a, 2021)	(a) MRI-based prostate segmentation: DIS, (b) retinal image-based optic cup and disc segmentation: DIS	Shape and semantics-based selective regularization to penalize changes of parameters with high joint shape and semantics-based importance
Zhu et al. (2023)	(a) Binary prostate segmentation from T2-weighted MRI scans collected from 6 sites: DIS, (b) cross-site and cross-modality 4-class abdominal segmentation between CT and MRI scans: DIS, (c) same-site cross-modality muscle segmentation of muscles and bones between MRI and mDixon scans: DIS	Knowledge distillation
Liu et al. (2023a)	Brain tumor segmentation: CIS with domain shift (3 Ep.)	Pseudo label-based knowledge distillation
Bai et al. (2023)	Surgical question answering: CIS	Regularization: knowledge distillation
Wu et al. (2024)	Image super-resolution: TIS (4 Ep.)	Regularization (knowledge distillation and parameter importance based gradient update)
Aslam et al. (2024)	Disease outbreak detection in time-series signal: DIS (10 Ep.)	Regularization (EWC)
Zhu et al. (2024b)	(a) MRI Prostate segmentation: DIS (b) MRI Cardiac segmentation: DIS	Regularization (knowledge distillation)

Table 10

List of various architecture based works in literature.

Reference (year)	Application & CL scenario	CL technique
Karani et al. (2018)	MR brain segmentation: DIS (4 Ep.)	Domain specific batch normalization layer
Bayasi et al. (2021)	Skin lesion image classification: DIS (6 Ep.)	Architecture (fixed but partitioned network: culprit unit pruning mechanism)
Memmel et al. (2021)	Brain MRI hippocampal segmentation: DIS (2 Ep.)	Architecture (feature disentanglement through adversarial training)
González et al. (2022)	MRI-based Hippocampus Segmentation: DIS (2 Ep.)	Architecture based approach based on out-of-distribution detection concept: maintain multivariate Gaussians for all past learning created on batch normalization layer
Yang et al. (2023a)	Skin disease classification on dermoscopic, clinical images: CIS (4-20 Ep.)	Pretrained feature extractor + class specific GMMs built on each deep feature
Verma et al. (2024)	Disease classification on (a) Fundus: TIS (2 Ep.), (b) pathology images: TIS (3 Ep.)	Architectural (Task specific model is trained, task id is inferred during inference)
Qazi et al. (2024)	(a) Disease classification in histopathology images: CIS (7 Ep.), (b) Skin lesion classification: CIS (4 Ep.)	Task specific adapter with merging facility to increase computational efficiency

5 (change of hue and saturation, simulating, for example, change of reagent manufacturer, scanner or stainer). Finally, authors used this augmented dataset for setting class-incremental, domain-incremental, data-incremental, as well as task-incremental scenarios.

Another line of research popularly uses MNIST or similar well-defined datasets instead of collecting real datasets for the evaluation of the CL model. In the medical field, there is a recently released (year 2021) MNIST-like collection of biomedical images offering dozens of datasets, termed MedMNIST (Yang et al., 2023c). Derakhshani et al. (2022) consider 4 MedMNIST datasets, including BloodMNIST, OrganaMNIST, PathMNIST, and TissueMNIST as 4 domains and curate 3 CL scenarios with it. These datasets are multi-class (8–11 classes in each) disease classification datasets from different imaging modalities and organs. Each dataset was split to have disjoint classes leading to a total of 4 episodes in each dataset. Task and class incremental scenarios were set up for each dataset separately. In the task incremental scenario, the aim was to evaluate only the classes from the current episode whereas in class incremental, the aim was to evaluate all seen classes. Thus the class incremental scenario is difficult than

task incremental. They term the datasets generated from different sites/imaging protocols as **cross-domain incremental** scenario, instead of domain-incremental. Here the evaluation is done across the 4 datasets (BloodMNIST, OrganaMNIST, PathMNIST, and TissueMNIST), i.e., each dataset is treated as an episode. Further authors presented domain-agnostic and domain-aware settings in this. Domain-agnostic case is more difficult than domain-aware as the domain ID is not explicitly provided in domain-agnostic.

4. Continual learning strategy

Owing to frequently encountered domain shifts in medical applications, CL strategies aim to tackle performance drop due to domain shifts and thus might become a necessity in clinical applications (Pi-anykh et al., 2020; Lee and Lee, 2020). All the available strategies for preventing catastrophic forgetting can be broadly categorized into three main categories: (a) rehearsal-based approaches where a small memory is used to store previous episode data in some form, (b) regularization-based methods where the aim is to control weight update to minimize

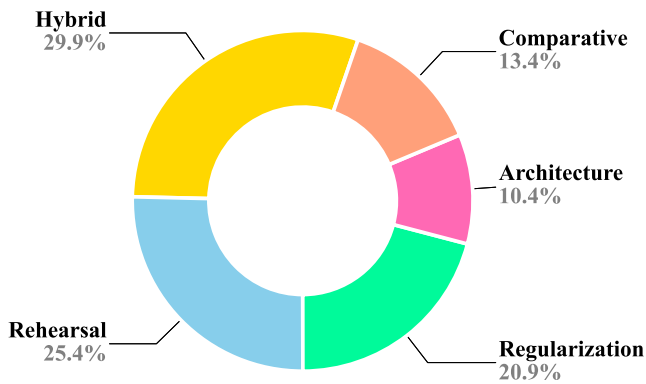


Fig. 5. Popularity of different CL strategies for medical image analysis.

forgetting the previous learning, (c) architectural-based methods which mainly aim to keep some network parameters isolated for each episode, and (d) hybrid category which offers various combination of any of these three categories. Fig. 6 presents a taxonomy of CL techniques and their adaptation in the medical field by various works. Further, the sub-technique category for each work is also mentioned in the figure. More detail of CL techniques in each work can be found in Table 8, Table 9, Table 10, Table 11, and Table 12 for rehearsal, regularization, architectural, hybrid, and comparative studies, respectively. Additionally, a pie chart showing the ratio of works falling in the above-mentioned categories is shown via Fig. 5. It indicates the popularity of using one or more strategies together in hybrid settings owing to better classification or segmentation performances in sequential learning. Now, we discuss each category in detail in the following sections.

4.1. Rehearsal based

This category of methods aims to approximate and recover old data distributions to augment with the new task data. Typically, there is a memory buffer to store data samples from past tasks, which are then used for replaying during the learning of a new task in order to retain previously learned knowledge and hence mitigate catastrophic forgetting. Here, the samples can be original images (Rebuffi et al., 2017; Karthik et al., 2022) or deep features (Van de Ven and Tolias, 2019) or generated pseudo samples (Shin et al., 2017) and can be selected via various heuristics and stored in memory buffer.

Based on the content of the memory buffer, the methods in this category can be broadly divided into the following sub-categories viz., (i) experience replay-based, (ii) generative replay-based, (iii) latent replay-based, and (iv) memory buffer optimization.

4.1.1. Experience replay-based

In experience replay, a few past exemplars (images) are stored in a small memory buffer. The main challenge here is to design a strategy to select important exemplars that will be stored in the limited storage to fully exploit the memory buffer.

For natural image classification, Rebuffi et al. (2017) proposed a popular experience-based method called incremental Classifier and Representation Learning (iCaRL) which is also highly explored for various medical applications, e.g., histopathology tumor classification (Kaustaban et al., 2022), disease classification (Derakhshani et al., 2022), etc. The iCaRL strategy has a fixed memory buffer condition where a subset of the most representative examples is maintained for each class, aiming to carry the most representative information of the class in the learned feature space. The distance between data instances in the latent feature space is used to update the memory buffer. During representation learning, both the stored samples and current task samples are utilized for training. During inference, a nearest-mean-of-exemplars classification strategy is used to assign the label to the class

with the most similar prototype. The original iCaRL method requires all data from the new task to be trained together. To address this limitation and enable the new instances from a single task to come at different time steps, Chaudhry et al. (2019) proposed Experience Replay (ER), which uses reservoir sampling to randomly sample a certain number of data instances from a data stream of unknown length, and store them in the memory buffer.

Further exploration has been conducted to select the most representative samples for replay in medical applications. Bera et al. (2023) propose a simple sample selection technique for binary segmentation with a memory bank of K samples, equi-distributed over the classes. Half of the exemplars are selected based on the occupancy of the positive class inside the image, i.e., the higher the content of the positive class, the higher the chance of being selected; the other half are selected based on their contribution to the learning process, i.e., if the gradient variation is more for a sample, then it is hard to learn and hence important. Hofmanninger et al. (2020a) propose to store samples based on their degree of uniqueness inferred using the Gram matrix computed on activations from the last convolution layer of the deep model. They evaluated the framework on chest CT data with synthetically generated domain shifts for classification application. To combat costly annotation in medical segmentation applications, Perkonigg et al. (2021, 2022) propose to combine rehearsal-based CL and active learning, where the model indicates important samples that need to be annotated rather than annotating all the samples. They detect domain shifts using a memory buffer for outliers, prompting the labeling of informative samples for model adaptation. Furthermore, it is important to note that storing raw samples in WSI analysis applications is highly memory-intensive due to the gigapixel size of each WSI. To address this challenge, Huang et al. (2023) propose a Breakup-Reorganize (BuRo) strategy, which stores only a subset of regions from a WSI instead of the entire image. During replay, a synthetic WSI is generated by randomly selecting and stitching stored regions from multiple WSIs. This approach not only reduces the memory burden of storing full WSIs in the buffer but also introduces data augmentation by creating diverse synthetic WSIs on the fly.

4.1.2. Latent replay-based

While experience replay requires storing the past samples in raw form, it can cause serious privacy violations in critical medical applications (Thandiackal et al., 2024; Zhu et al., 2024b; Bayasi et al., 2024b). Therefore, a less concerning direction, i.e., storing features instead of raw images, is also explored. For continual chest X-ray classification application in domain shift conditions, Srivastava et al. (2021) explore leveraging vector-quantization to store and replay hidden representations under memory constraints. Although not directly accessible, sharing of latent representations involves possible privacy threats through manipulation and reconstruction of actual sensitive medical data (Pennisi et al., 2023). Given access to a model and its latent space, a malicious entity could reverse-engineer a patient's medical record, violating privacy. Attackers might create adversarial instances to alter latent representations, potentially reconstructing crucial information from seemingly benign data. Reconstruction attacks (Newaz et al., 2020), membership inference attacks (Shokri et al., 2017), model inversion attacks (Fredrikson et al., 2015), etc., can be potential challenges associated with sharing of features. Models like GAN, auto-encoder, variational auto-encoder, etc, inherently possess the capability to regenerate raw data from latent spaces. Appropriate privacy measures like differential privacy (Abadi et al., 2016), privacy-preserved neural networks (Jovanovic et al., 2022), adversarial training (Yi et al., 2019), encryption and secure multi-party computation (Spini et al., 2024), etc. need to be considered to protect latent features during processing and sharing.



Fig. 6. The proposed CL taxonomy categorizes various CL models according to their underlying design principles. The abbreviations used are as follows: *ER* for Experience-replay, *GR* for Generative-replay, *LR* for Latent-replay, *PF* for Prior-focused, *DF* for Data-focused, and *MBO* for Memory Buffer Optimization. 1. Hofmanninger et al. (2020a), 2. Perkonigg et al. (2021), 3. Perkonigg et al. (2022), 4. Karthik et al. (2022), 5. Bera et al. (2023), 6. Huang et al. (2023), 7. Wei et al. (2023), 8. Sun et al. (2023a), 9. Zhu et al. (2024a), 10. Li et al. (2022), 11. Byun et al. (2023), 12. Wang et al. (2023a), 13. Thandiackal et al. (2024), 14. Srivastava et al. (2021), 15. Xiao et al. (2023), 16. Bringas et al. (2024), 17. Li and Jha (2023), 18. Baweja et al. (2018), 19. McClure et al. (2018), 20. van Garderen et al. (2019), 21. Zhang and Wang (2019b), 22. Özgün et al. (2020), 23. Zhang et al. (2021), 24. Zhang et al. (2023a), 25. Chen and Tang (2022), 26. Aslam et al. (2024), 27. Zhu et al. (2023), 28. Liu et al. (2023a), 29. Bai et al. (2023), 30. Zhu et al. (2024b), 31. Wu et al. (2024), 32. Karani et al. (2018), 33. González et al. (2022), 34. Yang et al. (2023a), 35. Verma et al. (2024), 36. Qazi et al. (2024), 37. Memmel et al. (2021), 38. Bayasi et al. (2021), 39. Ozdemir et al. (2018), 40. Ozdemir and Goksel (2019), 41. Chee et al. (2023), 42. Li et al. (2020b), 43. Ravishankar et al. (2019), 44. Liu et al. (2022), 45. Akundi and Sivaswamy (2022), 46. Zhang et al. (2023c), 47. Ji et al. (2023), 48. Shu et al. (2022), 49. Zhang et al. (2023b), 50. Sadafi et al. (2023), 51. Hua et al. (2023), 52. Sun et al. (2023c), 53. Ceccon et al. (2024b), 54. Ye et al. (2024), 55. Yang et al. (2023b), 56. Chen et al. (2023), 57. Li et al. (2024), 58. Bayasi et al. (2024b).

4.1.3. Generative replay-based

This category of approaches emerged as an alternative to experience replay, which highly violates privacy concerns with storing past samples and high memory buffer demands. Here, instead of a memory buffer of actual samples, there is a generative model that can generate samples, latent representation, both, or other information related to past tasks. This category of methods is also related to incremental learning of generative models where their incremental update is required. Hence, an additional requirement here is the continuous updating of the generative adversarial network. Since actual samples are not stored for replay, this category of approaches is also termed pseudo-rehearsal-based approaches.

To generate the past data, Li et al. (2022) employ a style-oriented replay module, which includes a base generative model trained on the first arrived domain and a style bank to record style adjustments for successive domains. Then, they incorporate the replayed past data to jointly optimize the model with current data to alleviate catastrophic forgetting. For continual semantic segmentation of MRI data emerging from different institutions, Memmel et al. (2021) train a model by

using all the simultaneously available datasets. Their method disentangles content from domain information through adversarial training, resulting in domain-invariant content representations. Other methods follow the sequential arrival of a dataset, i.e., one dataset at a time, whereas this work requires at least two datasets to start the feature disentanglement learning.

While generative replay has been widely explored in the natural image domain, medical applications face unique challenges, such as severe data scarcity and stringent privacy constraints. To address these challenges, recent studies have investigated lightweight generative models such as Gaussian Mixture Models (GMM) and Kernel Density Estimation (KDE) as alternatives to data-demanding GAN-based generators. Additionally, instead of directly generating raw images, there has been a growing focus on leveraging latent representations, which reduces the need to rely on large datasets, enhances generalization, and ensures privacy-aware solutions (Kumari et al., 2024b, 2025).

4.1.4. Memory buffer optimization

Experience replay-based approaches might overfit the stored sub-samples and seem to be bounded by joint training. Alternatively, memory buffer optimization-based approaches following constrained optimization provide solutions that have more scope for both plasticity and stability. The core idea is to guide the training of the current episode by utilizing the stored buffer samples from the past. Typically, the gradients of the current task are projected such that they do not negatively impact the gradients computed on the buffer samples. Thus, it is ensured that the model performs well on all previous episodes while learning a new episode. For example, the Gradient Episodic Memory (GEM) (Lopez-Paz and Ranzato, 2017) approach corrects the gradient computed on a mini-batch during stochastic gradient descent by utilizing an exemplar sample set from past episodes. This prevents changes that could degrade the performance of the network on the exemplar set. Further, the A-GEM approach (Chaudhry et al., 2018b) relaxes the projection in one direction computed by randomly selected samples from the memory buffer where both the buffer and sampling size are tunable hyper-parameters. There are some early attempts in this area in the medical realm. For example, for the fundus disease diagnosis problem, Shu et al. (2022) presents a gradient regularization approach for preventing forgetting and a replay-oriented consistency calculation method combined with a subspace weighting strategy to promote model adaptability. The authors employ gradient regularization in conjunction with a replay-oriented technique. The replay-oriented technique adaptively improves the update for incremental domains without carefully choosing exemplars for replay, whereas gradient regularization preserves information from previous ones.

4.2. Regularization-based

Rehearsal methods are quite popular due to their comparative better performance than other categories; however, the assumption of the availability of past data makes them less suitable for medical applications. In contrast, regularization-based approaches (Kirkpatrick et al., 2017; Schwarz et al., 2018; Zenke et al., 2017) avoid storing examples and mainly add a regularization term in the loss function or regularize the learning rate to penalize model updates that could lead to large deviation from an existing model, thus avoiding forgetting of learned knowledge.

Regularization-based methods can be categorized into data-focused and prior-focused approaches. Data-focused approaches (Silver and Mercer, 2002) distill the knowledge of old tasks to enhance the CL capabilities of the present model, whereas prior-based approaches such as Zenke et al. (2017), Kirkpatrick et al. (2017), Aljundi et al. (2018) define importance weights for the network's parameters. Based on these weights, a regularization loss is introduced that penalizes the shift of important parameters.

4.2.1. Prior-focused regularization

Prior-focused methods estimate the importance of all neural network parameters, used as prior when learning from new data. During the training of subsequent tasks, larger changes to important parameters are penalized. Elastic Weight Consolidation (EWC) (Kirkpatrick et al., 2017), initially designed for reinforcement learning in Atari games emerged as the first to establish the technique. EWC aims to constrain parameters of the model that are critical for performing previous tasks during the learning of the new tasks. It uses the Fisher information matrix to calculate parameter importance for a given domain. These parameters are then regularized to prevent catastrophic forgetting.

In the medical domain, Baweja et al. (2018) are the first to explore EWC to address the issue of catastrophic forgetting in neural networks when sequentially learning two distinct segmentation tasks (normal brain structure and white matter lesion). Specifically, the first task consists of multi-class segmentation of cerebrospinal fluid, grey matter,

and white matter, and the second task consists of segmentation of white matter lesions. The study demonstrates that EWC effectively reduces catastrophic forgetting in this challenging medical imaging context. Further, van Garderen et al. (2019) adopt EWC for glioma segmentation on different datasets in domain-shift arising from low and high-grade glioma in different datasets. In the context of histopathology breast cancer classification task, Chen and Tang (2022) showcase EWC capabilities for class incremental setting. McClure et al. (2018) introduce Distributed Weight Consolidation (DWC) as a CL method to consolidate weights of separate neural networks trained on independent datasets. Further, Zhang et al. (2023a) propose to compute the importance matrix jointly based on shape and semantics information in context for continual medical segmentation. The shape-based importance measures how sensitive a parameter is to shape properties in the images and semantics-based importance measures a parameter's sensitivity to reliable semantic predictions, ensuring that noisy or uncertain semantics do not influence the learning process. Then, the selective regularization scheme is applied to penalize updates to model parameters with high joint importance weights. This ensures that critical shape and semantic knowledge from previous sites is not overwritten or forgotten.

Another prior-focused strategy is Synaptic Intelligence (SI), which alleviates catastrophic forgetting by allowing individual synapses (i.e., neurons) to estimate their importance for solving a learned task. Similarly to EWC, the approach penalizes changes to the most relevant synapses so that new tasks can be learned with minimal forgetting (Zenke et al., 2017). A disadvantage is the need to distribute some extra parameters per weight in addition to their value, but in terms of data size, this is far less than providing the exemplars.

Apart from EWC and SI, various other methods have been contributed. Popularly, the Memory Aware Synapses (MAS) approach (Aljundi et al., 2017) calculates the importance of weights with a model of Hebbian learning in the biological system, which relies on the sensitivity of the output function and can hence be utilized in an unsupervised manner. For medical segmentation, Özgün et al. (2020) adapted MAS for brain MRI segmentation by addressing its instability in large networks. The surrogate loss in MAS was normalized by the number of network parameters to improve stability. Additionally, highly skewed importance weights caused training instability, which was mitigated by detecting and adjusting outliers using the interquartile range criterion, followed by normalization between zero and one for better interpretability. These modifications enhanced MAS's applicability to medical image segmentation, ensuring robust continual learning across domains. Yet another novel emerging direction is Orthogonal Weight Modification (OWM) Zeng et al. (2019), where the gradient of the current task is projected into the orthogonal direction to the subspace spanned by gradients of all previous tasks. Then parameter updates for the current task are permitted only in the orthogonal direction of the past episodes, thus protecting against interference with already learned knowledge.

4.2.2. Data-focused regularization

The data-focused regularization method (Li and Hoiem, 2017) aims to distill knowledge from a model trained on the previous tasks to the model trained on the new task in order to consolidate previously learned knowledge. Typically, the previous model acts as a teacher and the current model as a student while adopting knowledge-distillation (KD) (Gou et al., 2021) to avoid catastrophic forgetting. Usually, all the old data should be available in knowledge-distillation, which is not the case with CL; therefore, as an alternative, few old data, current data, or the generated old data are explored for the same. The loss function has an additional distillation loss for replayed data. Each input is replayed with a soft target obtained using the stored model.

Silver and Mercer (2002) first proposed to use previous task model outputs given new task input images, mainly for improving new task performance. Later, in natural image classification application, Li and Hoiem (2017) re-introduced the concept as the LwF technique. A copy

Table 11

List of various hybrid CL technique based works in literature.

Reference (year)	Application & CL scenario	CL technique
Ozdemir et al. (2018)	MRI-based Humerus and scapula segmentation: CIS (2 Ep.)	Knowledge distillation + experience replay + multi-head
Ozdemir and Goksel (2019)	MRI based knee segmentation: CIS (2 Ep.)	Knowledge distillation + experience replay + multi-head
Ravishankar et al. (2019)	Chest X-ray view classification: DIS (2 Ep.), TIS (2 Ep.), Pneumothorax identification from X-ray: IIS (4 batches, each of 2K)	Latent replay where samples are selected either randomly or importance based (farther from cluster centroids) + dynamic network (task specific feature transformer layers)
Li et al. (2020b)	Dermoscopic images based skin disease classification: CIS (4-20 Ep.)	Dual knowledge distillation (from old classifier (previous classes) and the fine-tuned classifier (a new FC layer fine-tuned on new classes)) + experience replay (fixed subset of data for each class is stored), during inference nearest-mean-of-exemplars method used for class prediction (Rebuffi et al., 2017) (where the mean is often calculated by averaging the feature vectors of the stored or selected subset of data in the feature space for each class)
Liu et al. (2022)	CT data based segmentation of abdomen organs: CIS (4 Ep.)	Rehearsal (latent replay) + regularization (knowledge distillation)
Akundi and Sivaswamy (2022)	Chest X-ray classification: CIS (5 Ep.)	Regularization (knowledge distillation) + architecture (task specific head)
Shu et al. (2022)	Fundus disease classification: DIS (2-4 Ep.)	Replay (memory buffer optimization) + regularization (gradient regularization)
Chee et al. (2023)	3 applications as (a) Cancer classification: CIS, (b) diabetic retinopathy classification: CIS, (c) skin lesions classification: CIS	Architecture (separate high-level descriptor for each task) + regularization (distillation loss) + replay (data based rehearsal, fixed memory per task)
Zhang et al. (2023c)	(a) Multi-organ segmentation: CIS, (b) abdomen segmentation to liver tumor segmentation: CIS	Architecture: organ specific segmentation head + pseudo labelling based knowledge distillation
Ji et al. (2023)	Multi-organ segmentation: CIS	Architecture: organ specific decoder + pseudo labelling based knowledge distillation
Zhang et al. (2023b)	Continual disease classification in different image modality settings: CIS	Experience replay + Architecture based (keeps task specific adapters and classifier heads)
Sadafi et al. (2023)	Dermoscopic WBC classification: DIS, CIS, DIS+CIS	Experience replay based rehearsal (representativeness of examples for each class and model uncertainty) + regularization (binary-cross entropy based distillation loss)
Yang et al. (2023b)	MedMNIST based disease classification: CIS+DIS (4 Ep.)	Generative replay+ data-focused regularization
Hua et al. (2023)	sEMG-based Gesture Classification: CIS (4 Ep.)	Rehearsal (experience replay) and Regularization (KD)
Chen et al. (2023)	3 separate applications including (a) Optic disc: DIS (3 Ep.), (b) cardiac: DIS (3 Ep.), (c) prostate segmentation: DIS (6 Ep.)	Rehearsal (GAN based generative replay) + Regularization (KD from past segmentation model)
Sun et al. (2023c)	Multi-class classification on time-series signals: CIS (4-10 Ep.)	Rehearsal (experience replay)+ Regularization (KD)
Li et al. (2024)	MR Cardiac segmentation: DIS (5 Ep.)	Rehearsal (privacy-aware generative replay with CGAN) + Architecture (ConvLSTM based domain-customised expansion block)
Ceccon et al. (2024b)	Chest X-ray disease classification: NIC (7 Ep.)	Pseudo-Labeling and memory buffer based replay
Bayasi et al. (2024b)	(a) Skin lesion classification: CIS (3 Ep.), DIS (4 Ep.), CIS+DIS (5 Ep.), (b) blood cell classification: CIS (4 Ep.), (c) Colon tissue classification: CIS (4 Ep.)	Architecture (fixed but partitioned network: culprit unit pruning mechanism) + Regularization (knowledge distillation from a generalized network to expert network to enhance generalizability)
Ye et al. (2024)	Multi-modal (medical report, MRI, X-ray, CT, histopathology) Representation learning: TIS (5 Ep.)	Rehearsal (K-means sampling based buffer creation for experience replay) + Regularization (MSE based knowledge distillation)

of the previous model parameters is stored before learning the new task, and then it is used to get the soft labels for the new task as the target from the classifiers of the previous tasks. The available ground truth is used as the target for the new task classifier. LwF has been adopted in various medical applications like incremental brain MRI segmentation (Ozdemir et al., 2018), chest X-ray classification (Lenga et al., 2020), disease classification (Derakhshani et al., 2022), histopathology tumor classification (Kaustaban et al., 2022), etc.

Other works in the natural image processing domain Jung et al. (2016), Zhang et al. (2020) have been introduced with LwF-related ideas; however, it has been shown that this strategy is vulnerable to domain shift between tasks (Aljundi et al., 2017). It was pointed out that LwF would not result in good performance if the data distributions between different tasks are quite diverse (Rannen et al., 2017). To overcome this, Rannen et al. (2017) facilitate incremental integration

of shallow auto-encoders to constrain task features in their corresponding learned low dimensional space. Hence, they further trained an autoencoder for each task to learn the most important features corresponding to the task and used it to preserve knowledge. Such multiple expert-based knowledge-distillation have proven effective in domain generalization application too (Niu et al., 2023). Student expert modules possess domain-specific information. Each expert also learns from all other students by knowledge-distillation technique to facilitate domain-invariant features. Also, when more emphasis is attributed toward improving unseen classes, i.e., forward transfer, CL based sequential learning of domains helps in domain generalization (Li et al., 2020a). Another adaptation of the LwF strategy in medical application was proposed by Sadegehi et al. (2025) for heterogeneous modality brain MRI segmentation. To address varying degrees of domain shift across tasks, a drift-based dynamic estimation of the regularization

Table 12

List of various comparative studies of CL techniques in literature.

Reference (year)	Application & CL scenario	CL technique
Lenga et al. (2020)	Chest X-ray classification: DIS (2 Ep.)	Comparative study: joint training, EWC, LwF
Morgado et al. (2021)	Dermatological imaging modality classification: DIS	Comparative study: Regularization (EWC), rehearsal based (AGEM, experience replay)
Derakhshani et al. (2022)	Disease classification: TIS, CIS, DIS (4 Ep.)	Regularization, memory-replay (comparative: EWC, MAS, LwF, iCaRL, EEIL)
Ranem et al. (2022)	MRI-based binary hippocampus segmentation: DIS (3 Ep.)	Comparative study: transformers with EWC fisher matrix (Kirkpatrick et al., 2017), EWC with Riemannian walk (Chaudhry et al., 2018a), Modeling the Background (knowledge distillation and a modified Cross Entropy Loss) (Cermelli et al., 2020), Pseudo-labeling and Local Pod (multi-scale spatial distillation loss with pseudo labeling) (Douillard et al., 2021), Pooled Outputs Distillation (Douillard et al., 2020)
Kaustaban et al. (2022)	Tumor classification: DIS, CIS, TIS, IIL	Regularization, replay (comparative study: EWC, LwF, CoPE, iCaRL, A-GEM)
Bándi et al. (2023)	Cancer detection across organs such as breast, colon, and head-neck: DIS	Comparative study of existing approaches: PackNet (architecture), EWC (regularization), GEM (rehearsal)
Verma et al. (2023)	Disease classification on (a) Fundus: CIS (3 Ep.), (b) pathology images: CIS (3 Ep.)	Comparative study of existing buffer-free (privacy-aware) approaches in three categories: Rehearsal (GR, BIR), Regularization (EWC, SI, MAS, MUC-MAS, RWalk, OWM, GPM, LwF, LwM), Architecture (EFT)
Kim et al. (2024)	Arrhythmia detection on ECG data: DIS (4 Ep.)	Comparative study of 3 existing regularization techniques (LwF, EWC, MAS)
Ceccon et al. (2024a)	Chest X-ray disease classification: CIS (5 Ep.)	Comparative study of approaches in regularization (LwF, pseudo-label), rehearsal (replay), hybrid (rehearsal+regularization) categories for fairness evaluation.

factor is introduced at each task, replacing the static regularization factor used in LwF.

4.3. Architecture-based

Architecture-based methods, also termed parameter isolation-based methods typically assign different parameters in a network to each task. This can be achieved by either fixing the architecture or dynamically extending the network (Mallya and Lazebnik, 2018; Hung et al., 2019; Mallya and Lazebnik, 2018; Fernando et al., 2017; Yoon et al., 2017). Fixed architectures are limited by the network's capacity, whereas dynamic architectures need more memory with every new task. Most fixed architectures-based methods assign different parts of the network for each task, which requires task identity during inference, but this identity information is usually unavailable.

In the fixed architecture category, Bayasi et al. (2021) proposes a CL strategy where a subset of the network units is assigned to learn each domain separately. Their approach introduces a novel pruning criterion that allows a fixed network to learn new data domains sequentially over time. They identify culprit units associated with wrong classifications in each domain and use them to learn the new domain while freezing the non-culprit nodes. Further, the authors introduce BiasPruner (Bayasi et al., 2024a), which extends their approach to mitigate gender, age, and ethnic bias in medical applications including skin lesion classification and chest X-ray classification. By pruning biased units, BiasPruner constructs de-biased sub-networks, enhancing both fairness and classification performance. Similarly, Mallya and Lazebnik (2018) propose to prune the weights with low magnitude and reuse them for the next task, while the remaining weights that are responsible for the previous tasks are kept unchanged. In architecture-based approaches, typically the old knowledge is not exploited to learn the new, thus preventing knowledge transfer from a related task which is an important factor in CL.

Some works aim to dynamically extend the feature extractor module by learning task-specific branches in it (Yan et al., 2021b). Rusu et al. (2016) propose to use a dynamic architecture that blocks any changes to the network trained on previous knowledge and expands the architecture by allocating sub-networks with a fixed capacity to be trained

with the new data, and thus it keeps a pool of pre-trained models, one for each learned task. In contrast, Aljundi et al. (2017) propose a network of experts where each expert is a model trained given a specific task and a set of gating autoencoders that learn a representation for the task at hand, and, at inference time, automatically forward the test sample to the relevant expert. Another dynamic expandable model direction given by Yoon et al. (2017) expands the network using group sparse regularization to decide how many neurons to add at each layer and perform selective retraining. Similarly, Karani et al. (2018) propose to use domain/task-specific batch norm layers to adapt to new MRI protocols while learning the segmentation of various brain regions. Entire batch-normalization layers were dedicated to modeling domain differences. However, this causes quadratic increase in parameters with new tasks. Moreover, as this approach dedicates specific batch-normalization parameters to each dataset/domain/task, task labels are necessary to determine to which dataset each sample belongs.

In contrast, González et al. (2022) investigate the performance of CL methods in a task-agnostic setting, which better simulates dynamic clinical environments characterized by gradual population shifts. They propose an out-of-distribution detection-based solution that signals when to expand the model and select the best parameters during inference. Specifically, they learn a multivariate Gaussian on the last batch normalization layer of the deep model and store it in the memory. When there is out-of-distribution detection or domain shift is alerted based on a threshold on Mahalanobis distance from existing Gaussian in the memory and the new data, a new Gaussian is added to the memory. The closest Gaussian is used for inference and thus eliminates the need for domain ID during inference.

Further, to address the high parameter demands of U-Net-based segmentation, Ranem et al. (2024) introduce NCAdapt, a Neural Cellular Automata (NCA)-based approach for CL in hippocampus segmentation tasks. Their method incorporates domain-specific adaptable convolutional layers into the NCA backbone, allowing a balance between plasticity and stability with a lightweight parameter structure. However, NCA-based methods require higher VRAM and longer training times due to the cell-based processing approach in NCA.

4.4. Hybrid techniques

Combining two or more individual CL strategies has recently gained interest owing to the enhanced performance gained by harnessing the merits of different CL strategies. [Ozdemir et al. \(2018\)](#) mitigate catastrophic forgetting for incremental medical segmentation applications using a distillation loss inspired by LwF ([Li and Hoiem, 2017](#)). Further, they extend the approach by incorporating memory-replay strategies and task-specific segmentation heads. Specifically, representative images were selected based on abstraction layer response and content distance in the last embedding layer. [Liu et al. \(2022\)](#) also use knowledge distillation and a memory buffer to store the prototypical representation of different organ categories. [Akundi and Sivaswamy \(2022\)](#) also keep class-specific classification head along with knowledge distillation to avoid forgetting for chest X-ray classification application where data arrives in class incremental fashion. A pseudo-rehearsal technique was combined with task-specific dense layers for pneumothorax classification ([Ravishankar et al., 2019](#)) by [Ravishankar et al. \(2019\)](#); however, it suffers from the linear increase of parameters and unbounded memory to store features for every domain.

[Li et al. \(2020b\)](#) introduce dual distillation as well as a fixed memory-based experience replay to continually learn the effective model. Specifically, they maintain an expert classifier, which is nothing but the previous model fine-tuned on new classes after replacing the old fully-connected layer with a new one. Then, a final classifier is distilled using the old classifier and the expert classifier. A fixed amount of old samples is also stored and replayed with current data while training the updated classifier. Then, the nearest-mean-of-exemplars (often calculated by averaging the feature vectors of the stored or selected subset of data in the feature space for each class) method is used for category prediction at the test time.

[Chee et al. \(2023\)](#) utilize the dynamic expanding network, regularization, as well as data replay for continually learning new classes. A low-level feature extractor is shared across tasks, but a high-level feature extractor is especially learned for each subsequent task. Further, an alternate training procedure so as to learn new classes, i.e., newly added high-level feature extractor (by freezing others) and learning the old classes (freezing the new task feature extractor) is followed. A fixed memory per task is kept to replay samples with current samples.

[Sadafi et al. \(2023\)](#) use experience replay-based rehearsal and binary cross-entropy-based regularization terms for mitigating catastrophic forgetting. There is fixed memory and each class has an equal contribution to it. The sampling strategy for exemplar selection for a specific class is twofold: half of the samples are selected based on their distance from the mean, i.e., the closest samples to the class mean are selected, and another half of the samples for the class are selected based on model's uncertainty for each sample as given in epistemic uncertainty estimation ([Mukhoti et al., 2021](#)).

[Zhang et al. \(2023c\)](#) exploit knowledge distillation as pseudo-labeling for old classes along with architecture-based CL strategy. In vanilla Swin UNETR architecture, they replace the conventional output layer responsible for segmentation with organ-specific light-weight segmentation heads, which thus enable independent predictions for any new or previously learned classes. Thus, there is a single encoder and decoder module and multiple organ-specific heads (few MLP layers) on the output of the encoder. In a similar fashion [Ji et al. \(2023\)](#) keep organ-specific encoder and apply knowledge distillation. They also apply network architecture search-based pruning on decoders to maintain network complexity. But in comparison to [Zhang et al. \(2023c\)](#) strategy, the network complexity of maintaining multiple decoders is very high.

[Zhang et al. \(2023b\)](#) propose a rehearsal and architecture-based approach. In order to effectively extract discriminative features from a pre-trained feature extractor for different diseases, a learnable lightweight adapter is added between consecutive convolutional stages at each subsequent task. Furthermore, each task-specific classification head is also added at each step. Then, in each task, the model aims to find optimal parameters in the newly added task-specific adapters and classification head using the training data from the new task (new disease) and preserve a small subset for each previously learned disease.

4.5. Comparative studies

There have been multiple comparative studies of different kinds of CL approaches on various applications like histopathology-based cancer detection ([Bándi et al., 2023](#)), histopathology-based tumor detection ([Kaustaban et al., 2022](#)), chest X-ray classification ([Lenga et al., 2020](#)), dermatological image modality classification ([Morgado et al., 2021](#)), etc. [Lenga et al. \(2020\)](#) show a comparative study of joint training and CL techniques such as EWC, and LwF to improve model adaptation to new chest X-ray domains arising from cross-sites while mitigating catastrophic forgetting effects. Upon model evaluation on two datasets from different sites (ChestX-ray14 and MIMIC-CXR) referring to domain shifts, the best results are achieved with joint training, but EWC and LwF offer practical solutions as the previous samples need not be stored with the CL approaches. In the digital pathology research field, [Kaustaban et al. \(2022\)](#) systematically evaluate various CL methods, including regularization-based and rehearsal-based approaches on self-augmented domain shift on the H&E dataset. The authors concluded that though regularization-based methods performed well for DIS and IIS, only the rehearsal-based method (iCaRL) is effective for CIS which is a more challenging scenario. Further, TIS may be even more challenging for digital pathology as compared to other image domains.

Further, with simulated datasets, i.e., MedMNIST (MNIST-like collections of biomedical images) various benchmark CL methods in rehearsal-based (iCaRL), regularization-based (EWC, MAS, LwF), and bias-correction method (EEIL) were evaluated under different CL scenarios ([Derakhshani et al., 2022](#)). For the majority of the experiments including CIS, TIS, and cross-DIS, the rehearsal-based approach, i.e., iCaRL shows the most promising results for disease classification. Further authors indicated that the existing CL methods which tend to do well in natural image applications (non-medical) may perform inadequately in medical disease classification applications due to their inherent complexity, such as the spatial locality of diseases. Similarly, in the case of a dermatological imaging modality classification problem under domain-shifted condition, [Morgado et al. \(2021\)](#) showed a comparison of EWC, averaged GEM, and experience replay. They concluded that MobileNetV2 with experience replay performs best among the others. [González et al. \(2023\)](#) also provided open-source implementation of five CL strategies including rehearsal, EWC, LwF, Riemannian Walk (RW), and Modeling the Background (MiB), on top of nnU-Net for various CL based applications like hippocampus, prostate, or cardiac segmentation.

5. Level of supervision

Here we provide a discussion on what level of supervision is considered and explored in literature while developing a CL method.

5.1. Task or domain ID

Most of the approaches specifically require information about task/domain ID, i.e., which task/domain the current samples belong to. This information is then used to select or activate the task-specific branch in the model for classification/segmentation/feature extraction. If task/domain ID is needed then the approach is regarded as (a) task/domain aware else (b) task/domain agnostic. However, a well-designed CL approach should not rely on a task/domain ID to perform prediction ([Aljundi et al., 2017](#); [Bayasi et al., 2021](#)). Most of the approaches presume a-priori knowledge of domain IDs ([Derakhshani et al., 2022](#); [Zhang et al., 2023c](#)) while some infer from the data ([Zhang et al., 2023b](#); [Bayasi et al., 2021](#); [Aljundi et al., 2017](#)). A very few do not require this information ([Derakhshani et al., 2022](#); [González et al., 2022](#); [Perkonig et al., 2022](#)).

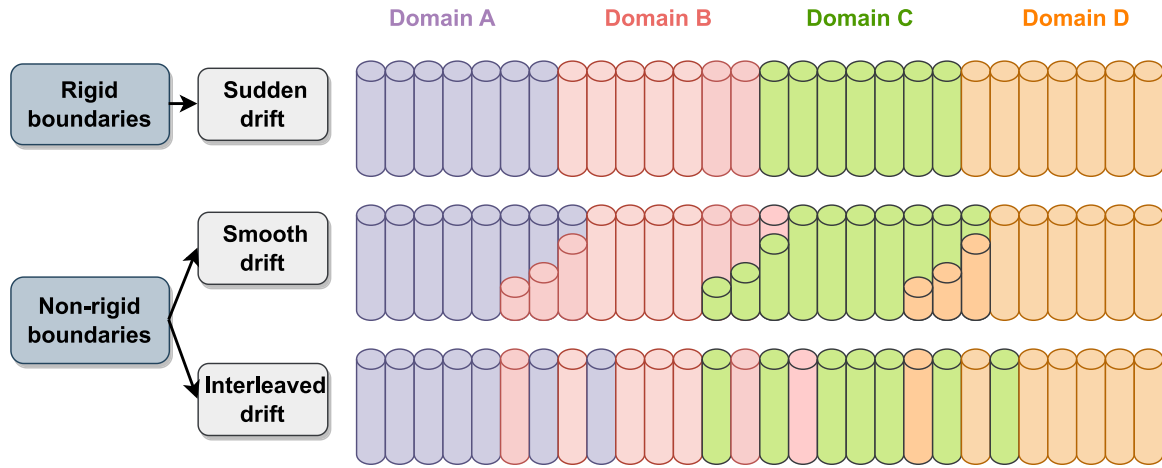


Fig. 7. A demonstration for rigid and non-rigid task/domain boundaries for an example sequence of four domains in a CL pipeline.

5.2. Task boundaries

Typically, a shift is regarded as a change of data source, i.e., datasets coming from different sites, acquisition environments, etc. Therefore, there are well-separated domain shifts or task boundaries. Thus, the necessary measures to adapt to the changed domain are triggered when there is a change in task/domain. Most of the works in the literature follow the assumption of well-separated task/domain boundaries.

However, in real-life cases, the change in domain/task could be interleaved or smooth rather than an abrupt transition. Such settings come under the umbrella of ‘blurred boundary continual learning’ (Wang et al., 2023b). To better visualize the rigid and non-rigid boundary-based sequence of domains, a demonstration is provided via Fig. 7. Recently a few works (Hofmanninger et al., 2020a; Srivastava et al., 2021; González et al., 2022; Perkonig et al., 2022) have explored such settings. For example, González et al. (2022) considers two kinds of non-rigid shifts in hippocampus segmentation datasets. In the first kind, termed ‘shifting source’, they create slowly shifting distributions with 3 datasets (HarP, Dryad, and Decathlon) by interleaving samples from these datasets for segmentation application. In another case termed ‘transformed’, they create shift using TorchIO library (Pérez-García et al., 2021) which performs various intensity rescaling and affine transform in the Decathlon dataset to create five episodes. Another example of a non-rigid boundaries-based CL scenario is given by Srivastava et al. (2021) for the chest X-ray classification problem. They consider 3 multi-site datasets (NIH Chest-X-rays14, PadChest, and CheXpert) as 3 domains; however, they curate a smooth transition from one dataset to another at the boundaries.

5.3. Sample annotation

Apart from information regarding the task IDs, annotation for the samples in tasks is also a major concern. Almost all the available CL strategies in the medical domain require sample annotation for learning the classification or segmentation task. It is undeniable that labeling is highly costly in the medical domain, especially in the histopathology field, and hence may hinder the rapid advancement of the field. In other domains, unsupervised CL strategies have been explored; for example, Ashfahani and Pratama (2022) use only a few labeled samples to associate clusters to classes and the learning is completely unsupervised.

6. Evaluation strategy and metrics

To evaluate a CL strategy, various aspects can be explored such as the performance of the model on past, current, or future episodes, resource consumption (Zhang et al., 2023c), memory size (Hofmanninger

	Te1	Te2	Te3	Te4
Tr1	P11	P12	P13	P14
Tr2	P21	P22	P23	P24
Tr3	P31	P32	P33	P34
Tr4	P41	P42	P43	P44

Fig. 8. Train-test performance matrix.

et al., 2020a), model size growth, execution time, etc. CL frameworks involving dynamic architecture or memory also report time and memory analysis. For example, González et al. (2022) maintains model history as mean and variance parameters of multivariate Gaussian, which dynamically grow in the presence of drift; hence, the authors also provide a training time analysis. If the framework does not involve a dynamic architecture, primarily performance on data is reported. Further, the performance of data mainly involves evaluating and reporting the episode performance, stability, and plasticity.

In CL, there is a given sequence of episodes $(1, \dots, T)$ to learn sequentially. Typically, we have well-defined training and test pairs (Tr_i, Te_i) for each i th episode. Upon sequential training, a **train-test performance matrix** $P \in P^{T \times T}$ is generated for the given sequence of episodes $(1, \dots, T)$. An example matrix for $T = 4$ is shown in Fig. 8. The cell $P_{t,i}$ refers to the performance on test data of the i th episode when the model training up to the t th episode is complete. Thus, after training up to t th episodes, the performance values $P_{t,i}$ for $i < t$, $i = t$, and $i > t$ correspond to performances on past, current, and future episodes, respectively.

The performance metric is chosen depending on the application. For example, IoU, Dice score/coefficient, structural similarity, Hausdorff distance, average symmetric surface distance, etc., are popular choices for segmentation, whereas accuracy, recall, F1-score, and AUC are usually computed for classification applications. AUC and F1-score are commonly used in medical continual learning due to the prevalence of class-imbalanced datasets, ensuring robust evaluation of model performance, especially in detecting rare pathological cases. Once the performance metric is chosen, we can compute metrics for measuring stability and plasticity on top of it. Various metrics have been proposed to quantify stability (Table 13) and plasticity (Table 14); however, all the metrics are derived from the same train-test performance matrix (Fig. 8) to measure the amount of forgetting or forward transfer.

Table 13

Metrics for backward transfer. For ease of readability, terms in equations are color-coded to refer to the corresponding cells in the matrix (last column).

Reference	Eq.	Equation	Pictorial representation																									
Lopez-Paz and Ranzato (2017)	Eq.(A)	$\frac{1}{T-1} \sum_{i=1}^{T-1} (P_{T,i} - P_{i,i})$	<table><tr><th></th><th>Te1</th><th>Te2</th><th>Te3</th><th>Te4</th></tr><tr><th>Tr1</th><td>P11</td><td>P12</td><td>P13</td><td>P14</td></tr><tr><th>Tr2</th><td>P21</td><td>P22</td><td>P23</td><td>P24</td></tr><tr><th>Tr3</th><td>P31</td><td>P32</td><td>P33</td><td>P34</td></tr><tr><th>Tr4</th><td>P41</td><td>P42</td><td>P43</td><td>P44</td></tr></table>		Te1	Te2	Te3	Te4	Tr1	P11	P12	P13	P14	Tr2	P21	P22	P23	P24	Tr3	P31	P32	P33	P34	Tr4	P41	P42	P43	P44
	Te1	Te2	Te3	Te4																								
Tr1	P11	P12	P13	P14																								
Tr2	P21	P22	P23	P24																								
Tr3	P31	P32	P33	P34																								
Tr4	P41	P42	P43	P44																								
Derakhshani et al. (2021)	Eq.(B)	$\frac{1}{T-1} \sum_{i=1}^{T-1} \max_{j=1}^{T-1} (P_{j,i} - P_{T,j})$	<table><tr><th></th><th>Te1</th><th>Te2</th><th>Te3</th><th>Te4</th></tr><tr><th>Tr1</th><td>P11</td><td>P12</td><td>P13</td><td>P14</td></tr><tr><th>Tr2</th><td>P21</td><td>P22</td><td>P23</td><td>P24</td></tr><tr><th>Tr3</th><td>P31</td><td>P32</td><td>P33</td><td>P34</td></tr><tr><th>Tr4</th><td>P41</td><td>P42</td><td>P43</td><td>P44</td></tr></table>		Te1	Te2	Te3	Te4	Tr1	P11	P12	P13	P14	Tr2	P21	P22	P23	P24	Tr3	P31	P32	P33	P34	Tr4	P41	P42	P43	P44
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Tr1	P11	P12	P13	P14																								
Tr2	P21	P22	P23	P24																								
Tr3	P31	P32	P33	P34																								
Tr4	P41	P42	P43	P44																								
Chee et al. (2023)	Eq.(C)	$\frac{1}{T-1} \sum_{i=2}^T \left(\frac{1}{i-1} \sum_{j=1}^{i-1} \max_{j>i} (P_{j,i} - P_{i,j}) \right)$	<table><tr><th></th><th>Te1</th><th>Te2</th><th>Te3</th><th>Te4</th></tr><tr><th>Tr1</th><td>P11</td><td>P12</td><td>P13</td><td>P14</td></tr><tr><th>Tr2</th><td>P21</td><td>P22</td><td>P23</td><td>P24</td></tr><tr><th>Tr3</th><td>P31</td><td>P32</td><td>P33</td><td>P34</td></tr><tr><th>Tr4</th><td>P41</td><td>P42</td><td>P43</td><td>P44</td></tr></table> Example for t=3		Te1	Te2	Te3	Te4	Tr1	P11	P12	P13	P14	Tr2	P21	P22	P23	P24	Tr3	P31	P32	P33	P34	Tr4	P41	P42	P43	P44
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Tr1	P11	P12	P13	P14																								
Tr2	P21	P22	P23	P24																								
Tr3	P31	P32	P33	P34																								
Tr4	P41	P42	P43	P44																								
Díaz-Rodríguez et al. (2018)	Eq.(D)	$\frac{1}{T-1} \sum_{i=1}^{T-1} \left(\frac{1}{ \{t_j\}_{j>i} } \sum_{j>i} (P_{j,i} - P_{i,j}) \right)$	<table><tr><th></th><th>Te1</th><th>Te2</th><th>Te3</th><th>Te4</th></tr><tr><th>Tr1</th><td>P11</td><td>P12</td><td>P13</td><td>P14</td></tr><tr><th>Tr2</th><td>P21</td><td>P22</td><td>P23</td><td>P24</td></tr><tr><th>Tr3</th><td>P31</td><td>P32</td><td>P33</td><td>P34</td></tr><tr><th>Tr4</th><td>P41</td><td>P42</td><td>P43</td><td>P44</td></tr></table>		Te1	Te2	Te3	Te4	Tr1	P11	P12	P13	P14	Tr2	P21	P22	P23	P24	Tr3	P31	P32	P33	P34	Tr4	P41	P42	P43	P44
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Tr3	P31	P32	P33	P34																								
Tr4	P41	P42	P43	P44																								
Özgün et al. (2020)	Eq.(E)	$\frac{2}{T(T-1)} \sum_{i=2}^T \sum_{j=1}^{i-1} \max (P_{i,j} - P_{j,i}, 0)$	<table><tr><th></th><th>Te1</th><th>Te2</th><th>Te3</th><th>Te4</th></tr><tr><th>Tr1</th><td>P11</td><td>P12</td><td>P13</td><td>P14</td></tr><tr><th>Tr2</th><td>P21</td><td>P22</td><td>P23</td><td>P24</td></tr><tr><th>Tr3</th><td>P31</td><td>P32</td><td>P33</td><td>P34</td></tr><tr><th>Tr4</th><td>P41</td><td>P42</td><td>P43</td><td>P44</td></tr></table> Example for t=3		Te1	Te2	Te3	Te4	Tr1	P11	P12	P13	P14	Tr2	P21	P22	P23	P24	Tr3	P31	P32	P33	P34	Tr4	P41	P42	P43	P44
	Te1	Te2	Te3	Te4																								
Tr1	P11	P12	P13	P14																								
Tr2	P21	P22	P23	P24																								
Tr3	P31	P32	P33	P34																								
Tr4	P41	P42	P43	P44																								

Table 14

Metrics for forward transfer. For ease of readability, terms in equations are color-coded to refer to the corresponding cells in the matrix (last column).

Reference	Eq.	Equation	Pictorial representation																									
Lopez-Paz and Ranzato (2017)	Eq.(F)	$\frac{1}{T-1} \sum_{i=2}^T (P_{i-1,i} - \bar{b}_i)$	<table><tr><th></th><th>Te1</th><th>Te2</th><th>Te3</th><th>Te4</th></tr><tr><th>Tr1</th><td>P11</td><td>P12</td><td>P13</td><td>P14</td></tr><tr><th>Tr2</th><td>P21</td><td>P22</td><td>P23</td><td>P24</td></tr><tr><th>Tr3</th><td>P31</td><td>P32</td><td>P33</td><td>P34</td></tr><tr><th>Tr4</th><td>P41</td><td>P42</td><td>P43</td><td>P44</td></tr></table>		Te1	Te2	Te3	Te4	Tr1	P11	P12	P13	P14	Tr2	P21	P22	P23	P24	Tr3	P31	P32	P33	P34	Tr4	P41	P42	P43	P44
	Te1	Te2	Te3	Te4																								
Tr1	P11	P12	P13	P14																								
Tr2	P21	P22	P23	P24																								
Tr3	P31	P32	P33	P34																								
Tr4	P41	P42	P43	P44																								
González et al. (2022)	Eq.(G)	$\frac{1}{T-1} \sum_{i=2}^T \left(\frac{1}{ \{t_j\}_{j \leq i} } \sum_{j \leq i} (P_{j,i} - P_{j-1,i}) \right)$																										
Shu et al. (2022)	Eq.(H)	$\frac{1}{T-1} \sum_{i=2}^T (P_{i,i} - P_{1,i})$	<table><tr><th></th><th>Te1</th><th>Te2</th><th>Te3</th><th>Te4</th></tr><tr><th>Tr1</th><td>P11</td><td>P12</td><td>P13</td><td>P14</td></tr><tr><th>Tr2</th><td>P21</td><td>P22</td><td>P23</td><td>P24</td></tr><tr><th>Tr3</th><td>P31</td><td>P32</td><td>P33</td><td>P34</td></tr><tr><th>Tr4</th><td>P41</td><td>P42</td><td>P43</td><td>P44</td></tr></table>		Te1	Te2	Te3	Te4	Tr1	P11	P12	P13	P14	Tr2	P21	P22	P23	P24	Tr3	P31	P32	P33	P34	Tr4	P41	P42	P43	P44
	Te1	Te2	Te3	Te4																								
Tr1	P11	P12	P13	P14																								
Tr2	P21	P22	P23	P24																								
Tr3	P31	P32	P33	P34																								
Tr4	P41	P42	P43	P44																								
Díaz-Rodríguez et al. (2018)	Eq.(I)	$\frac{2}{T(T-1)} \sum_{i=1}^{T-1} \sum_{i>j} P_{i,i}$	<table><tr><th></th><th>Te1</th><th>Te2</th><th>Te3</th><th>Te4</th></tr><tr><th>Tr1</th><td>P11</td><td>P12</td><td>P13</td><td>P14</td></tr><tr><th>Tr2</th><td>P21</td><td>P22</td><td>P23</td><td>P24</td></tr><tr><th>Tr3</th><td>P31</td><td>P32</td><td>P33</td><td>P34</td></tr><tr><th>Tr4</th><td>P41</td><td>P42</td><td>P43</td><td>P44</td></tr></table>		Te1	Te2	Te3	Te4	Tr1	P11	P12	P13	P14	Tr2	P21	P22	P23	P24	Tr3	P31	P32	P33	P34	Tr4	P41	P42	P43	P44
	Te1	Te2	Te3	Te4																								
Tr1	P11	P12	P13	P14																								
Tr2	P21	P22	P23	P24																								
Tr3	P31	P32	P33	P34																								
Tr4	P41	P42	P43	P44																								
Chaudhry et al. (2018a)	Eq.(J)	$\frac{1}{(T-1)} \sum_{i=2}^T (P_{i,i} - b_i)$	<table><tr><th></th><th>Te1</th><th>Te2</th><th>Te3</th><th>Te4</th></tr><tr><th>Tr1</th><td>P11</td><td>P12</td><td>P13</td><td>P14</td></tr><tr><th>Tr2</th><td>P21</td><td>P22</td><td>P23</td><td>P24</td></tr><tr><th>Tr3</th><td>P31</td><td>P32</td><td>P33</td><td>P34</td></tr><tr><th>Tr4</th><td>P41</td><td>P42</td><td>P43</td><td>P44</td></tr></table>		Te1	Te2	Te3	Te4	Tr1	P11	P12	P13	P14	Tr2	P21	P22	P23	P24	Tr3	P31	P32	P33	P34	Tr4	P41	P42	P43	P44
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Tr3	P31	P32	P33	P34																								
Tr4	P41	P42	P43	P44																								

6.1. Stability: Backward transfer

Backward transfer (BWT) refers to measuring the catastrophic forgetting of a model upon learning new episodes. A model is regarded as stable if it gives a similar performance for an already learned episode over time. However, upon learning the new episode naively, it is possible to forget the past learning and hence disrupt the performance of the previous episode. In contrast, a carefully designed CL strategy will cause less forgetting or improvement on past episodes upon learning the new episodes. A BWT metric is used to measure the amount of forgetting. In other words, it is a way to measure stability, i.e., how well the model would retain the previously acquired knowledge to prevent catastrophic forgetting.

Lopez-Paz and Ranzato (2017) define BWT as the influence of new learning t_i task on a previous task. When learning a task t_i increases the performance on a previous task, it is *+ve* BWT, and if it causes deterioration, it results in *-ve* BWT. Large *-ve* BWT is also termed as catastrophic forgetting. The BWT metric given by Lopez-Paz and Ranzato (2017) is very frequently adopted (Srivastava et al., 2021; Hofmanninger et al., 2020a) and it is computed after finishing all the episodes as shown in Eq.(A) in Table 13. Average forgetting (Derakhshani et al., 2021) is another popularly used metric (Derakhshani et al., 2022; Chen and Tang, 2022). It is computed as the average of the difference in highest performance, and the final performance reached after training on all episodes is finished (Eq.(B) in Table 13). Chee et al. (2023) compute BWT after learning each subsequent task (r th) rather than computing it at the last episode (Eq.(B) in Table 13) as shown through Eq.(C) in Table 13. Díaz-Rodríguez et al. (2018) compute BWT as the change in performance after training with each subsequent task averaged over the number of tasks (Eq.(D) in Table 13). Note that BWT is not defined for the last task. Another BWT metric contribution is by Özgün et al. (2020) as shown via Eq.(E) in Table 13. Ideally, CL approaches should result in positive backward transfer, but given the complexity of medical tasks, especially segmentation applications, as compared to natural domain, achieving a positive BWT is challenging in buffer-free CL settings (González et al., 2023). Therefore, in addition to measuring positive BWT, stability quantified as *Remembering* (REM) metric ($\frac{2}{T(T-1)} \sum_{t=2}^T \sum_{i=1}^{t-1} (1 - |\min(P_{t,i} - P_{i,i}, 0)|)$) is also explored for brain MRI segmentation (Özgün et al., 2020).

6.2. Plasticity: Forward transfer

The plasticity of a model is reflected in its capability to accommodate more and more knowledge or exploit the knowledge learned so far to learn the new. In literature, this is frequently referred to as forward transfer (FWT). It is also said that FWT measures the “zero-shot” learning capability of a model (Lopez-Paz and Ranzato, 2017). In contrast to the usage of BWT, not all works report FWT. Certain approaches might enforce rigorous regularization on the model to get a comparatively reduced level of forgetting (high *+ve* BWT); however, this results in poor performance on new tasks. Therefore, reporting FWT along with BWT is equally important for unbiased evaluation of the CL model.

The very popular FWT metric (Srivastava et al., 2021; Hofmanninger et al., 2020a) shown via Eq.(F) in Table 14 is proposed by Lopez-Paz and Ranzato (2017) that quantifies FWT as the impact of learning a task t_i on a future task. It is the average of the difference in the performance on t_i task before learning it and the performance given by a model with random weights (b_i). Note that FWT is not defined for the first task. Further, González et al. (2022) computes FWT as the change in performance in each stage before and up to T_r , averaged over the number of tasks (Eq.(G) in Table 14). Another metric for FWT was proposed by Shu et al. (2022) as shown via Eq.(H) in Table 14. Díaz-Rodríguez et al. (2018) and Özgün et al. (2020) measure FWT as average performance of the model on unseen tasks, calculated as the mean of the elements above the diagonals in P (Eq.(I) in Table

14). While this metric does not directly assess the CL capabilities, it serves as a crucial measure of the model’s ability to generalize to unseen tasks. Chaudhry et al. (2018a) define FWT on seen episodes as reported via Eq.(J) in Table 14. Here, b_i is the performance by a standalone model only trained on the i th episode. Özgün et al. (2020) report a “transfer-learning metric” as the sum of diagonal elements in matrix P as measure of plasticity, i.e., the ability to adapt to new tasks.

6.3. Episode performance and others

Average accuracy (Derakhshani et al., 2021) is computed as the model performance after training up to r th episode. At any time t , the average performance is the mean of accuracy values for episodes $(1, \dots, t)$ as below:

$$\frac{1}{t} \sum_{i=1}^t P_{t,i} \quad (1)$$

Thus, after processing all episodes, we get a total of T average accuracy values which can be plotted and visualized for different approaches (Derakhshani et al., 2022; Kaustaban et al., 2022). Further, researchers (Derakhshani et al., 2022) also compute the mean over these values ($\frac{1}{T} \sum_{i=1}^T [\frac{1}{t} \sum_{i=1}^t P_{t,i}]$) to obtain a single scalar value which can be used to directly compare with other approaches. Another popular definition of average accuracy is to compute the above-mentioned metric only after finishing all the episodes (Lopez-Paz and Ranzato, 2017; Chen and Tang, 2022; Kaustaban et al., 2022) as below.

$$\frac{1}{T} \sum_{i=1}^T P_{T,i} \quad (2)$$

There have been efforts to combine plasticity and stability measures in medical CL, to compare algorithms with a single metric. Given the complexity of medical applications (in contrast to the natural image domain), improving performance on the current dataset is more relevant than on unseen data. Therefore, researchers measure plasticity as transfer-learning metric which signifies how well the model learns the current dataset (average of diagonal values in P). The combination of this transfer-learning metric with backward transfer (element below the diagonal of P) is proposed as incremental-learning (IL) or continual-learning metric for medical application (Özgün et al., 2020; Li et al., 2022); for example for segmentation application it is represented as IL-DSC or CL-DSC.

7. Discussion: Towards the future

Our exploration of CL methods for medical imaging reveals a multitude of challenges and strategies. The extant literature reflects a struggle with traditional paradigms, notably the need for explicit task/domain identification. While some methods require prior knowledge of domain IDs, others explore task/domain-agnostic approaches that aim to eliminate this dependency (Aljundi et al., 2017; Bayasi et al., 2021). The evolving notion of task/domain boundaries adds another layer of complexity, with real-world scenarios often defying the assumption of well-separated shifts. Non-rigid transitions and blurred boundaries, as explored by González et al. (2022), Wang et al. (2023b), pose challenges to existing CL approaches. Sample annotation, a common requirement for CL in medical imaging, introduces resource challenges, especially in histopathology. While supervised strategies dominate, Ashfahani and Pratama (2022) showcase the feasibility of unsupervised CL, using minimal labeled samples. The evaluation of CL strategies involves a diverse set of metrics, including stability (backward transfer - BWT) and plasticity (forward transfer - FWT). These metrics, encompassing aspects such as average forgetting and incremental learning, facilitate nuanced comparisons. In the classification domain, applications such as chest X-rays and skin disease classification employ diverse CL strategies. Latent replay mitigates catastrophic

Table 15

Literature for CL based classification. (**) indicates non-imaging modality.

Reference (year)	Imaging modality	Application	CL scenario	CL strategy	Model	Learning type	Evaluation metric	Dataset
Ravishankar et al. (2019)	X-ray, Ultrasound	(a) Cardiac view classification, (b) Pneumothorax identification	DIS, TIS, IIS	Rehearsal + Architectural	CNN	Supervised	Accuracy, BWT	Subset of ChestXRay (Wang et al., 2017)
Hofmanninger et al. (2020a)	CT	Classification of synthetic object in chest images	DIS	Rehearsal	Res-Net50 (He et al., 2016)	Supervised	Accuracy, BWT, FWT	Private
Lenga et al. (2020)	X-ray	Chest X-ray classification	DIS	Comparative: EWC, LWF	DenseNet121 (Huang et al., 2017)	Supervised	AUC, BWT, FWT	ChestX-ray14, MIMIC-CXR
Li et al. (2020b)	Dermoscopic	Skin disease classification	CIS	Regularization + Rehearsal	ResNet18, AlexNet, VGG19	Supervised	Accuracy	Skin8, Skin40 from ISIC2019 (Tschandl et al., 2018), CIFAR100
Srivastava et al. (2021)	X-ray	Chest X-ray classification	DIS	Rehearsal	ResNet101	Supervised	AUC, FWT, BWT	NIH Chest-X-rays14 (McDermott et al., 2020), PadChest (Bustos et al., 2020), CheXpert (Wang et al., 2017)
Bayasi et al. (2021)	Dermoscopic	Skin lesion classification	DIS	Architectural (fixed but partitioned network)	ResNet-50	Supervised	Accuracy	HAM10000 (Tschandl et al., 2018), Dermofit (Ballerini et al., 2013), Derm7pt (Kawahara et al., 2018), MSK (Codella et al., 2018), PH2 (Mendonça et al., 2013), UDA (Codella et al., 2018)
Morgado et al. (2021)	Dermoscopic	Dermatological imaging modality classification	DIS	Regularization, rehearsal	VGG-16, MobileNetV2	Supervised	Accuracy, precision, recall, F1-score, FWT, BWT	Private
Shu et al. (2022)	Fundus images	Eyes disease classification	DIS	Rehearsal + Regularization	Resnet-18, 2-layer MLP (Saha et al., 2021)	Supervised	F1-score, BWT, FWT	ODIR, RIADD, REFUGE, iSee (Fang et al., 2020), EyeQ (Fu et al., 2019), PMNIST (Rupesh Kumar et al., 2013)
Akundi and Sivaswamy (2022)	X-ray	Chest X-ray classification	CIS	Regularization	DenseNet121	Supervised	AUC, BWT	CheXpert
Kaustaban et al. (2022)	Histopathology	Tumor classification (breast cancer, colorectal cancer)	IIS, DIS, CIS, TIS	Regularization, Rehearsal (comparative:EWC, LwF, AGEM, CoPE, iCaRL)	ResNet-18	Supervised	Accuracy, FWT, BWT	CRC (Kather et al., 2019), PatchCam (Bejnordi et al., 2017)
Chen and Tang (2022)	Histopathology	Breast cancer identification	CIS	Regularization	Alexnet, Densenet201, Resnet152	Supervised	Accuracy, forgetting	BreakHis
Derakhshani et al. (2022)	Multiple	Multiple disease classification	TIS, CIS, cross-DIS	Regularization, Rehearsal (comparative: EWC, MAS, LwF, iCaRL, EEIL)	ResNet18	Supervised	Accuracy, forgetting	MedMNIST (Yang et al., 2023c)
Chee et al. (2023)	Histopathology, retinal, skin lesions	(a) Colorectal cancer detection, (b) diabetic retinopathy classification, (c) skin lesion classification	CIS	Rehearsal + Architecture + Regularization	ResNet18	Supervised	Accuracy, forgetting	CCH5000 (Kather et al., 2016), EyePACS (Anon, b), HAM10000 (Tschandl et al., 2018)
Zhang et al. (2023b)	Multiple	Disease classification (multiple organ source)	CIS	Rehearsal + Architectural	ResNet18	Supervised	MCR	Skin8, Path16, CIFAR100
Bándi et al. (2023)	Histopathology	Cancer detection cross organs (breast, colon, head-neck)	DIS	Comparative: (Architecture: PackNet) (Regularization: EWC, GEM)	DenseNet	Supervised	FROC, ROC, Cohen's Kappa	CAMELYON16, CAMELYON17, private for colon and head-neck
Bai et al. (2023)	VQA	Surgical visual-question localized-answering	CIS	Regularization	VisualBERT	Supervised	Accuracy, IoU	EndoVis18, EndoVis17, M2CAI
Sadafi et al. (2023)	Microscopic	WBC classification	DIS, CIS, DIS + CIS	Rehearsal + Regularization	ResNeXt-50	Supervised	Accuracy	Matek-19 (Matek et al., 2019), INT-20, and Acevedo-20 (Acevedo et al., 2020)
Yang et al. (2023b)	Multiple	Disease classification	DIS+CIS	Rehearsal	ResNet18	Few-shot	Accuracy, performance dropping rate	MedMNIST (Yang et al., 2023c) (PathMNIST, DermaMNIST, OrganAMNIST, RetinaMNIST, BreastMNIST, BloodMNIST)
Byun et al. (2023)	2D fundus, dermoscopic	(a) Diabetic retinopathy severity classification, (b) skin lesion classification	DIS	Rehearsal	ViT-B/16	supervised	AUC, backward transfer	fundus (Messidor-2, APTOS), skin lesion (BCN2000, PAD-UEFS-20, HAM10000)

(continued on next page)

forgetting but increases resource consumption, while knowledge distillation balances stability and plasticity (Li et al., 2020b; Srivastava et al., 2021). Segmentation tasks, spanning brain sclerosis lesion segmentation to cardiac segmentation, rely on regularization techniques such as EWC and knowledge distillation (Karthik et al., 2022; Li et al., 2022). The simultaneous handling of classification and segmentation tasks, evident in studies on dermoscopic image-based skin disease classification (Li et al., 2020b) and abdominal organ segmentation (Liu et al., 2022), introduces a trade-off between resource efficiency and overall model performance. The synthesis of literature and comparative analyses unveils the current state of CL in medical imaging. However, challenges persist, and future research should explore unsupervised CL, address labeling costs, and refine evaluation metrics. As the field evolves, understanding the dynamic interplay between medical imaging tasks and CL methodologies will be crucial for driving innovation. In Tables 15–17, we present the overview of the selected publications

in the domain of classification, segmentation, and both combined, respectively. We highlight the domain/application, dataset information, imaging modalities, CL scenarios, and strategies, including the learning process and methodology adopted/proposed by different studies. From the last year (2023), we also witness some exploration in non-imaging medical applications including disease classification, gesture classification, arrhythmia detection, etc. Further, apart from classification and segmentation, applications such as super-resolution (Wu et al., 2024), WSI retrieval (Zhu et al., 2024a), representation learning (Ye et al., 2024), etc., also benefit from CL. Based on our critical analysis of existing literature, we discuss some of the open challenges and thus possible research directions for CL in the medical field.

Non-imaging or other applications Recently, there have also been explorations in wearable medical sensor data. For example, Hua et al. (2023) explore experience replay (various sample selection strategies were explored) and knowledge distillation (on old data) based CL for incrementally learning gesture classes with sEMG data. Similarly, Sun

Table 15 (continued).

Reference (year)	Imaging modality	Application	CL scenario	CL strategy	Model	Learning type	Evaluation metric	Dataset
Xiao et al. (2023)	dermoscopic & clinical images	Skin disease classification	CIS	Rehearsal (Memory buffer optimization)	ResNet-18	Few-shot	accuracy, sensitivity, and specificity	private curated from various public sources (ISIC-2018, ISIC-2019, ISIC-2020, SD-198, SD-256, PAD-OFED-20, Asan, Hally, etc.)
Yang et al. (2023a)	Dermoscopic, clinical	Skin disease classification	CIS	Architectural	ResNet101 + GMMs	Supervised	MCR	Skin7 (Codella et al., 2018), Skin40 (Sun et al., 2016)
Verma et al. (2023)	(a) Fundus, (b) pathology	Disease classification	CIS	Comparative (Rehearsal, Regularization, Architecture)	ResNet50	Supervised	MCR	(a) OCT (Kermany et al., 2018), (b) PathMNIST (Yang et al., 2023c)
Huang et al. (2023)	WSI	Tumor subtype classification	CIS	Rehearsal	ConvNeXt (image encoder) + transformer (classifier)	supervised	BWT, AUC, Masked AUC, Accuracy	4 datasets (NSCLC, BRCA, RCC, ESCA) from TCGA ^a project
Hua et al. (2023)	sEMG**	Gesture classification	CIS	Rehearsal+ Regularization	CNN	supervised	Accuracy, Remember	Ninapro DB2 (Atzori et al., 2014)
Sun et al. (2023a)	time-series signals**	Mortality identification, Sepsis identification	CIS	Rehearsal	LSTM	online	BWT, FWT, AUC, Accuracy	COVID-19 (Yan et al., 2020), SEPSIS (Seymour et al., 2017)
Sun et al. (2023c)	time-series signals**	Multi-class classification	CIS	Rehearsal + Regularization	1D-ConvNet	few-shot	Accuracy, relative performance drop rate	Mit-BIH (Goldberger et al., 2000), FaceAll (Dau et al., 2019), UWave (Dau et al., 2019), Mit-BIH Long-Term ECG (Goldberger et al., 2000)
Li and Jha (2023)	Physiological signals**	Disease classification	DIS, CIS, TIS	Rehearsal	MLP	Supervised	Accuracy, F1 score, BWT	CovidDeep(Hassantabar et al., 2021), DiabDeep(Yin et al., 2019), MHDeep(Hassantabar et al., 2022)
Kim et al. (2024)	ECG**	Arrhythmia detection	DIS	Comparative (Regularization: LwF, EWC, MAS)	1D-CNN+MLP	Supervised	AUC	(Zheng et al., 2020), (Wagner et al., 2020), (Alday et al., 2020), (Liu et al., 2018)
Aslam et al. (2024)	Time series signal**	Disease classification	DIS	Regularization (EWC)	LSTM	Supervised	Accuracy, forgetting	Mpox (Mathieu et al., 2022), Influenza (Anon, d), and Measles (Anon, e)
Ceccon et al. (2024b)	X-ray	Chest disease classification	NCI	Rehearsal + Regularization	–	Supervised	AUC, F1 score, forgetting	ChestX-ray14(Wang et al., 2017), CheXpert(Irvin et al., 2019)
Verma et al. (2024)	(a) Fundus, (b) histopathology	Disease classification	TIS	Architectural	ResNet50	Supervised	Accuracy	(a) OCT (Kermany et al., 2018), (b) PathMNIST (Yang et al., 2023c)
Bayasi et al. (2024b)	(a) Dermoscopic, (b) microscopic, (c) histopathology	(a) Skin lesion classification, (b) blood cell classification, (c) Colon tissue classification	CIS, DIS, CIS+DIS	Regularization + Architectural	ResNet50	Supervised	Avg. recall, forgetting, AUROC	(a) HAM10000 (Tschandl et al., 2018), Dermofit (Ballarini et al., 2013), Derm7pt (Kawahara et al., 2018), MSK (Codella et al., 2018), UDA (Codella et al., 2018), BCN (Combalia et al., 2019), PH2 (Mendonça et al., 2013) (b) PBS-HCB (Acevedo et al., 2020), (c) NCT-CRC-HE (Kather et al., 2019)
Ceccon et al. (2024a)	X-ray	Chest disease classification	CIS	Comparative (Regularization, Rehearsal, hybrid)	ResNet50	Supervised	AUC, TPR gap	ChestX-ray14 (Wang et al., 2017), CheXpert (Irvin et al., 2019)
Thandiackal et al. (2024)	Histopathology	Tissue classification	DIS	Rehearsal	ResNet18	Unsupervised	F1 score	K-19 (Kather et al., 2016), K-16 (Kather et al., 2019), CRC-TP (Javed et al., 2020)
Qazi et al. (2024)	(a) Histopathology, (b) dermoscopic	Disease classification	CIS	Architectural	ResNet18	Supervised	Accuracy, FLOPS	Skin8, Path16
Bringas et al. (2024)	Time-series (motion-sensor)**	Alzheimer's disease stage identification	IIS (2 Ep., 3 Ep., 4 Ep.)	Rehearsal	1D-CNN	Supervised	Accuracy, F1-score, forgetting	private

^a <https://www.cancer.gov/ccg/research/genome-sequencing/tcga>

et al. (2023a,b) incrementally learn classes from time series signals (ECG, categorical data) for applications including time-series health monitoring, mortality identification, sepsis identification, gesture classification, etc. Further, there have been studies to handle domain shifts due to multi-site data (Kim et al., 2024), patient-level splits (Li and Jha, 2023), data distributional shifts (change in mean and standard deviation) (Aslam et al., 2024) in ECG, physiological signal, or other time-series data for disease classification and arrhythmia detection.

Largely CL has been explored for mainstream applications such as classification and segmentation, but some other application, such as image reconstruction, registration, translation, generation, anomaly detection, etc., can also benefit from CL techniques. Recently, Wu et al. (2024) explored CL for the image super-resolution task across different imaging modalities including PD, T1, and T2 weighted MRI, and X-ray is learned in a continual manner with a single super-resolution model. Notably, to deal with forgetting, authors use the idea of constraining gradient updates according to the importance of parameters as well as adding a distillation loss as a regularization.

Availability of benchmark datasets: Contrary to other natural imaging fields, there are no standard benchmark datasets for CL in the medical field. Therefore, a fair comparison of different research advancements made in the field is challenging. MedMNIST is an attempt to provide an MNIST-like dataset for the medical field, however, it is limited by its non-complex nature of various sub-datasets and not mainly developed for CL. Hence, it does not offer various drift

conditions that a CL technique could be explored to evaluate and quantify.

Intense labor requirements: Most of the CL approaches are supervised in nature and thus demand large annotated datasets for sequential training. This creates a bottleneck in model development especially in the histopathology domain as it is the most expensive in terms of annotation. To cope with a limited labeling budget in problems such as cardiac segmentation, lung nodule detection, and brain age estimation, Perkonig et al. (2022, 2021) explored an active learning strategy within the CL framework. The model indicates important samples and then only those samples are annotated by the experts. On the other hand, there are fully unsupervised CL approaches (Ke et al., 2022; Pratama et al., 2021; Ashfahani and Pratama, 2022) or self-supervised CL approaches (Liu et al., 2023b) in other domains that should be explored here to tackle the annotation scarcity problem.

Unexplored distributional changes: In the medical realm, drifts arising from covariance shifts are mainly explored that too by incorporating datasets from different centers or acquisition protocols for the same task. Thus, the type of drift is always “sudden drift” and easier to handle. On the other hand, there are many realistic unexplored drift settings. For example, drift within the center is close to a realistic scenario as it gives rise to smooth drift scenarios (Perkonig et al., 2022). Further, some drifts occur temporarily; for example, Bichlmayer et al. (2022) observe one novel kind of domain shift in kidney-CAM-model data (Bichlmayer et al., 2022), even if they follow a fixed acquisition

Table 16
Literature for CL based segmentation.

Reference (year)	Imaging modality	Application	CL scenario	CL strategy	Model	Learning type	Evaluation metric	Dataset
Karani et al. (2018)	MRI	Brain	DIS	Architecture	U-Net	Supervised	DSC	HCP (Van Essen et al., 2013), ADNI (ADNT), ABIDE (Di Martino et al., 2014) and IXI (IXI)
Baweja et al. (2018)	MRI	Brain structure segmentation (normal, white matter lesions)	TIS	Regularization: EWC	DeepMedic 3D convnet (Kamnitsas et al., 2017)	Supervised	DSC coefficient	UK Biobank (Miller et al., 2016)
McClure et al. (2018)	SMRI	Brain structure segmentation (axial and sagittal)	DIS	Regularization: DWC	MeshNet (Fedorov et al., 2017) (CNN-based)	Supervised	DSC	HCP (Van Essen et al., 2013), NKI (Nooner et al., 2012), Buckner (Biswal et al., 2010), WU120 (Power et al., 2017)
Ozdemir et al. (2018)	MRI	Segmentation of humerus and scapula	CIS	Regularization (LwF) + rehearsal	U-Net	Supervised	DSC, SSD	Private
Ozdemir and Goksel (2019)	MRI	Knee segmentation	CIS	Regularization	U-Net	Supervised	DSC, MSD	SK110 MICCAI Grand Challenge (Heimann et al., 2010)
van Garderen et al. (2019)	4 MR sequences: pre- and post-contrast T1w, T2w, & T2w FLAIR	Brain tumor segmentation	DIS	Regularization: EWC	3D U-Net CNN	Supervised	Dice score	BraTS 2018 (Bakas et al., 2017; Menze et al., 2014), private
Özgün et al. (2020)	MRI	Brain MRI segmentation	DIS	Regularization: MAS	QuickNAT (Roy et al., 2019)	Supervised	CL-DSC, REM, BWT+, TL, FWT	CANDI (Kennedy et al., 2012), MALC (Asman and Landman, 2013), and ADNI (Jack Jr. et al., 2008)
Memmel et al. (2021)	MRI	Hippocampal segmentation	DIS		U-Net	Supervised	IoU, DSC	(Simpson et al., 2015), (Kulaga-Yoskovitz et al., 2015), (Boccardi et al., 2015)
Perkonigg et al. (2021)	MRI	Brain MRI segmentation	DIS	Rehearsal	3D-ModelGenesis (Zhou et al., 2021b)	Supervised	MAE, FWT, BWT	IXI (IXI), OASIS3 (LaMontagne et al., 2019)
Ranem et al. (2022)	MRI	Hippocampus segmentation	DIS	Comparative (rehearsal, regularization, hybrid)	ViT U-Net	Supervised	DSC, FWT, BWT	Decathlon (Antonelli et al., 2022), Drayd (Denovellis et al., 2021), HarP (Boccardi et al., 2015)
Liu et al. (2022)	CT	Organ segmentation (liver, spleen, pancreas, right kidney left kidney)	CIS	Rehearsal + regularization	nnUNet	Supervised	DC, HD95	(Anon, a; Simpson et al., 2019), KITS (Heller et al., 2019) + private
Karthik et al. (2022)	MRI	Multiple sclerosis lesions (brain) segmentation	DIS	Rehearsal	3D U-Net	Supervised	DSC, BWT	(Kerbrat et al., 2020)
González et al. (2022)	MRI	Hippocampus segmentation	DIS	Architectural	nnUNet (Isensee et al., 2021)	Supervised	DSC, FWT, BWT	HarP (Boccardi et al., 2015), Dryad (Kulaga-Yoskovitz et al., 2015), Decathlon (Simpson et al., 2019)
Li et al. (2022)	CMR	Cardiac segmentation	DIS	Rehearsal	U-Net	Supervised	DSC, HD95, BWT, FWT	M&Ms (Campello et al., 2021)
Zhang et al. (2023a, MRI 2021)		(a) Prostate segmentation, (b) optic cup and disc segmentation	DIS	Regularization	U-Net	Supervised	DSC, ASSD	RUNMC (Bloch et al., 2015), BMC (Bloch et al., 2015), HCRUDB (Lemaître et al., 2015), UCL (Litjens et al., 2014), BIDMC (Litjens et al., 2014), HK (Litjens et al., 2014), (Sivaswamy et al., 2015; Fumero et al., 2011; Orlando et al., 2020)
Zhang et al. (2023c)	CT	(a) Abdomen multi-organ segmentation, (b) abdomen to liver tumor segmentation	CIS	Architectural	Swin UNETR (Hatamizadeh et al., 2021)	Supervised	Average DSC	BTCV (Landman et al., 2015), LiTS (Bilic et al., 2023), JHH (Xia et al., 2022) (private)
Ji et al. (2023)	3D CT	Whole-body organ segmentation	CIS	Architectural	nnUNet	Supervised	DSC HD95	TotalSegmentator (Wasserthal et al., 2023), ChestOrgan, HNOrgan, EsoOrgan (3 private)
Bera et al. (2023)	MRI	Prostate segmentation, hippocampus segmentation, spleen segmentation	TIS, DIS	Rehearsal	Residual UNet	Supervised	DSC, average forgetting, BWT, accuracy	(Prostate158 (Adams et al., 2022), NCI-ISBI (Anon, c), Promise12 (Litjens et al., 2014), Decathlon (Antonelli et al., 2022)), (Drayd (Denovellis et al., 2021), HarP (Boccardi et al., 2015)), (Spleen dataset in Decathlon (Anon, c))
Zhu et al. (2023)	CT, MRI	(a) Abdomen segmentation, (b) muscles segmentation, (c) prostate segmentation	DIS	Regularization	U-Net	Supervised	DSC, ASSD	Prostate (Liu et al., 2020a; Bloch et al., 2015; Lemaître et al., 2015), abdomen (Anon, a; Kavur et al., 2021), muscles (Zhu et al., 2021)
Liu et al. (2023a)	MRI	Brain tumor segmentation	CIS + domain shift	Regularization	ResNet-based 2D nnU-Net	Supervised	DSC, HD95	BraTS2013 (Menze et al., 2014), TCIA (Clark et al., 2013), CBICA (Bakas et al., 2018)
Wang et al. (2023a)	Endoscopic images	(a) Endoscopy segmentation, (b) surgical instrument segmentation	CIS	Rehearsal + regularization	ResNet101	Supervised	mIoU	EDD2020 (Ali et al., 2021, 2020), EndoVis18 (Allan et al., 2020), EndoVis17 (Allan et al., 2019)
Wei et al. (2023)	MRI	Brain tumor segmentation	IIS	Rehearsal	UNet	Supervised	DSC	LGG Segmentation (Buda et al., 2019)
Chen et al. (2023)	Fundus, MRI	(a) Optic disc segmentation, (b) cardiac segmentation, (c) prostate segmentation	DIS	Rehearsal + Regularization (KD)	UNet	Unsupervised	DSC	(a) REFUGE (Orlando et al., 2020), IDRid (Porwal et al., 2018), RIM-ONE DL (Batista et al., 2020), (b) M&Ms challenge datasets (Campello et al., 2021), (c) RUNMC (Liu et al., 2020a), NCI-ISBI13 (Bloch et al., 2015), I2CVB (Lemaître et al., 2015), PROMISE12 (Litjens et al., 2014)
Li et al. (2024)	MRI	Cardiac segmentation	DIS	Rehearsal + Architecture	Res-UNet	Supervised	DSC, BWT, FWT	ACDC (Bernard et al., 2018), M&M (Campello et al., 2021)
Zhu et al. (2024b)	MRI	(a) Prostate segmentation (b) Cardiac segmentation	DIS	Regularization	UNet	Supervised	HD95, DSC, BWT	(a) RUNMC (Bloch et al., 2015), BMC (Bloch et al., 2015), I2CVB (Lemaître et al., 2015), UCL (Litjens et al., 2014), BIDMC (Litjens et al., 2014), HK (Litjens et al., 2014), (b) M&M (Campello et al., 2021)

protocol. The tissue structure in histopathology data of mouse kidneys shows degradation over time, which causes the segmentation problem to be harder over time. Another very important kind of unexplored drift is “concept shift” or “concept drift”, which refers to a situation where the shift causes a change in the relationship of the input variable with

its target value (Lu et al., 2018; Kumari and Saini, 2022; Bhatt et al., 2022; Kumari, 2021). For example, in the context of diabetic patient identification, consider a scenario where individuals aged 30–50 are deemed likely to be diabetic patients. However, if, for unforeseen reasons or based on lifestyle and food habits, there is a shift in the severity

Table 17

CL Literature for classification + segmentation and other application.

Reference (year)	Imaging modality	Application	CL scenario	CL strategy	Model	Learning type	Evaluation matrices	Dataset
Zhang and Wang (2019b)	Longitudinal MRI	Alzheimer's disease progression modelling (regression)	TIS (7 Ep.)	Regularization	MLP	Supervised	wCC, PCC, rMSE	ADNI-1 (Jack Jr. et al., 2008),
Perkonig et al. (2022)	CMR, CT, MRI	Cardiac segmentation, lung nodule detection, brain age estimation	TIS	Rehearsal	2D-UNet, Faster R-CNN, ResNet-50	Supervised	Dice score, AP, MAE	Cardiac (Campello et al., 2021), LIDC (Setio et al., 2017) + LND challenge (Pedrosa et al., 2019), IXI (IXI) + OASIS-3 (LaMontagne et al., 2019)
Wu et al. (2024)	(PD, T1, T2) weighted MRI, X-ray	Super-resolution	TIS	Regularization	HAN (Niu et al., 2020)	Supervised	SSIM, PSNR, BWT, forgetting, Intransigence (plasticity)	IXI (IXI), Chest X-ray (Wang et al., 2017)
Ye et al. (2024)	Multi-modality (medical report, MRI, X-ray, CT, histopathology)	Representation learning	TIS (5 Ep.)	Rehearsal + Regularization	Transformer	Self-supervised	DSC, HD95, AUC, accuracy, F1-score	MIMIC-CXR 2.0.0 (Johnson et al., 2019), ADNI-1+ADNI-2+ADNI-GO (Jack Jr. et al., 2008), DeepLesion (Yan et al., 2018), TCGA
Zhu et al. (2024a)	Histopathology	WSI retrieval	CIS (4 Ep.)	Rehearsal	TransMIL (Shao et al., 2021)	Supervised	KRC, SRC, slide-level mean AP	TCGA

level and the age group to 20–50, it would be considered a concept drift for diabetic patient identification. This implies a fundamental change in the underlying patterns and characteristics associated with diabetic patients, thus influencing the performance and reliability of machine learning models.

Scalability for large-Scale medical datasets: Scalability emerges as a critical challenge in the context of CL for medical imaging, particularly as datasets continue to grow in size and complexity (Gonzalez et al., 2020). Efficient strategies are needed to handle the scale of large medical datasets, considering both computational resources and model complexity. Research efforts, as explored by Zhang et al. (2023c), should focus on optimizing model architectures, memory management, and training algorithms to ensure scalability without compromising performance.

Interpretable and explainable models: The interpretability and explainability of CL models constitute another open challenge in the medical imaging domain Rymarczyk et al. (2023). As highlighted in De-rakhshani et al. (2022), models used in clinical settings should not only achieve high performance but also provide meaningful insights into decision-making processes. Future research directions should prioritize the development of CL methodologies that can offer explanations for their predictions, fostering trust and acceptance in the clinical community.

Ethical considerations and patient privacy: Ethical considerations and patient privacy concerns are paramount in CL for medical imaging. The use of patient data for model training raises ethical questions regarding consent, data anonymization, and potential biases. Future research, in alignment with ethical guidelines discussed by Chee et al. (2023), should prioritize the development of frameworks that ensure responsible data usage, privacy preservation, and ethical guidelines. Striking a balance between innovation and the protection of patient rights is imperative for the sustainable progress of CL in medical imaging. Verma et al. (2023) stress over exemplar-free CL approaches for colon pathology and retina data-based disease classification. They present a comparative study of 12 existing approaches in all three major categories offering privacy-aware solutions. Specifically, they use LwF (Li and Hoiem, 2018), LwM Dhar et al. (2019), EWC (Kirkpatrick et al., 2017), SI (Zenke et al., 2017), MAS (Aljundi et al., 2017), MUC-MAS (Liu et al., 2020b), RWalk (Chaudhry et al., 2018a), OWM (Zeng et al., 2019), and GPM (Saha et al., 2021) in regularization category, GR (Shin et al., 2017) and BIR (Van de Ven et al., 2020) in generative replay category, and EFT (Verma et al., 2021) in architecture-based category.

Limitations with Gigapixel WSIs: The high resolution of whole slide images (WSIs), often 50,000 × 50,000 pixels, presents significant computational challenges for deep learning model design. The variability in WSI imaging technology and staining protocols affects model performance on new data, requiring continual adaptation of WSI analysis methods (Lai et al., 2024). Directly applying standard CL approaches to hierarchical WSI models can lead to severe knowledge forgetting of previously seen datasets. Additionally, WSIs are gigapixel

images with only slide-level labels, making storage and computation for rehearsal-based CL impractical due to limited memory. Huang et al. (2023) proposed a CL method, “ConSlide”, to progressively update a hierarchical WSI analysis architecture using sequentially acquired heterogeneous WSI datasets. In this approach, a representative set of past datasets is stored and periodically reorganized and replayed during model updates using an asynchronous updating mechanism. Thandi-ackal et al. (2024) proposed a rehearsal-based domain incremental scenario with unsupervised learning for tissue classification in WSIs patches. They utilize the generative feature-driven image replay in conjunction with a dual-purpose discriminator. Further, Zhu et al. (2024a) enhance reservoir sampling for WSI retrieval by incorporating distance consistency-based rehearsal.

Continual learning in diffusion models: The integration of CL into diffusion models (Kazerouni et al., 2023) represents a promising avenue for advancing the capabilities of these models in dynamic and evolving environments. Diffusion models, widely employed in diverse fields, including image processing and medical imaging, often face challenges when confronted with changing data distributions. CL techniques can play a pivotal role in allowing these models to adapt and accumulate knowledge over time, ensuring sustained performance in the face of evolving datasets and tasks. By incorporating CL, diffusion models can enhance their adaptability and generalizability, making them more resilient to variations in data characteristics and distribution shifts (Gao and Liu, 2023). This approach can significantly contribute to the robustness and effectiveness of diffusion models in real-world applications.

Continual learning in implicit neural representations: The exploration of CL within implicit neural representations (Molaei et al., 2023) opens up new frontiers in leveraging the power of neural networks for dynamic learning scenarios. Implicit neural representations refer to a class of models where functions, such as geometric shapes or scenes, are represented as continuous signals rather than discrete entities (Sitzmann et al., 2020). These representations are commonly used in generative modeling and function approximation due to their ability to capture complex, high-dimensional data in a compact form (Molaei et al., 2023). Implicit neural representations can benefit immensely from CL techniques to adapt to new data and tasks seamlessly. As the data landscape evolves, implicit neural representations face challenges related to retaining past knowledge and efficiently incorporating new information (Po et al., 2023; Yan et al., 2021a). CL offers a solution to these challenges by enabling models to update their representations while preserving previously acquired knowledge. This not only enhances the model's ability to handle changing data distributions but also supports the development of intelligent systems that can learn and evolve over time. CL in implicit neural representations is instrumental in creating adaptable and intelligent models that can navigate the complexities of dynamic environments.

8. Conclusion

It has been proved and accepted by the research community that traditional machine learning models are ill-suited to handle the dynamic nature of data, and CL offers a promising solution. The systematic review in this manuscript provides a comprehensive overview of the state-of-the-art research in the field of CL in medical image analysis. We have explored various aspects of this evolving topic, including the challenges posed by changing data distributions, hardware, imaging protocols, data sources, tasks, and concept shifts in clinical practice and the need for models to adapt seamlessly. Through a meticulous analysis of the existing literature, we have examined the CL scenarios, strategies, level of supervision, experimental setup, evaluation schemes, and metrics employed to deal with the drifting nature of medical image data. Furthermore, diverse applications of CL in medical image analysis are discussed, ranging from disease classification and detection to intricate tasks of image segmentation. Each application area presents unique challenges and opportunities for research and development, and our review has shed light on the progress made in these domains. Additionally, a thorough collection and analysis of various evaluation matrices for forward and backward transfer facilitate robust evaluation and benchmarking of approaches.

In conclusion, this systematic review provides valuable insights into the current state of CL adaptation in medical image processing tasks, unexplored challenges, and promising future research directions. As medical image analysis technology continues to advance, the development of CL models will be crucial for improving diagnostic accuracy, patient care, and overall healthcare outcomes.

CRedit authorship contribution statement

Pratibha Kumari: Conceptualization, Writing – original draft. **Joohi Chauhan:** Writing – original draft, Writing – review & editing, Supervision. **Afshin Bozorgpour:** Writing – review & editing. **Boqiang Huang:** Writing – review & editing. **Reza Azad:** Writing – review & editing. **Dorit Merhof:** Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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