An Empirical Review of Deep Learning Frameworks for Change Detection: Model Design, Experimental Frameworks, Challenges and Research Needs

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Abstract—Visual change detection, aiming at segmentation of video frames into foreground and background regions, is one of the elementary tasks in computer vision and video analytics. The applications of change detection include anomaly detection, object tracking, traffic monitoring, human machine interaction, behavior analysis, action recognition, and visual surveillance. Some of the challenges in change detection include background fluctuations, illumination variation, weather changes, intermittent object motion, shadow, fast/slow object motion, camera motion, heterogeneous object shapes and real-time processing. Traditionally, this problem has been solved using hand-crafted features and background modelling techniques. In recent years, deep learning frameworks have been successfully adopted for robust change detection. This article aims to provide an empirical review of the state-of-the-art deep learning methods for change detection. More specifically, we present a detailed analysis of the technical characteristics of different model designs and experimental frameworks. We provide model design based categorization of the existing approaches, including the 2D-CNN, 3D-CNN, ConvLSTM, multi-scale features, residual connections, autoencoders and GAN based methods. Moreover, an empirical analysis of the evaluation settings adopted by the existing deep learning methods is presented. To the best of our knowledge, this is a first attempt to comparatively analyze the different evaluation frameworks used in the existing deep change detection methods. Finally, we point out the research needs, future directions and draw our own conclusions.

Index Terms—Change detection, survey, background subtraction, deep learning, scene independence

I. INTRODUCTION

Change detection (CD) in video streams is an essential task in computer vision with numerous applications in video synopsis generation [1], [2], anomaly detection [3], object tracking [4], [5], traffic monitoring [6], human machine interaction [7], behavior analysis [8], action recognition [9], and visual surveillance [10], [11]. The aim of a CD algorithm is to segment a video frame into foreground and background regions. Such pre-processed video frames are frequently used in higher-level tasks as discussed above. Since the outcome of the CD algorithm has a great impact on the overall performance of subsequent steps in high-level applications. Therefore, it is crucial that the method produce as robust foreground/background segmentation as possible. One of the strengths of CD algorithms is that it is completely free from the requirement of manual target or object mask initialization by the user. The onus of background initialization and maintenance for identifying the foreground objects is also put on the CD method [12]. Thus, the CD algorithms can also assist the visual object tracking methods in assigning the target objects for further processing. However, designing a robust CD method is a very challenging task due to numerous real world challenges discussed earlier.

Application of CD in intelligent transportation systems: The tremendous advancement in deep learning has fueled breakthrough in several computer vision applications for intelligent transportation systems (ITS). The video-based analytics are often preferred in developing ITS over other modalities (such as a LIDAR) due to its lower cost and ease in accessibility. As a low-level video task, change detection or moving object detection is commonly used in autonomous driving [13], anomaly detection [14], [15], traffic analysis [16], and intelligent surveillance [17], [18]. However, various real-world scenarios such as fluctuation in background regions, illumination variation, shadow, heterogeneous object shapes, variable frame rate of different cameras, weather changes, intermittent object motion, camera jitter and variable object motion make change detection a very challenging task [19], [20], [20], [21]. Furthermore, for real-time applications in various mobile devices, it is imperative that the CD methods function at very high speed with minimal resource requirements [22], [23]. These challenges have been partially addressed (independently or collectively) in the literature. Our detailed review and analysis of the existing deep CD methods is an important contribution for ITS applications.

Overall, the CD methods can be categorized into traditional and learning-based approaches. The traditional methods could be further grouped into parametric [25], [26], non-parametric [28], [33] and hybrid/other methods based on the background subtraction techniques used to model background behavior and identify foreground region using various thresholding techniques. The growth in the performance of the traditional approaches over the benchmark CDnet 2014 dataset is shown in Fig. [1] The learning-based methods are further divided into supervised and unsupervised approaches. The most significant improvement in performance is led by the recent convolutional neural networks (CNN) designed for

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supervised change detection. In this paper, we primarily focus on the characteristics of these deep learning based methods and their generalization capabilities to real-world unseen videos. In Fig. 2a and Fig. 2b, we depict the evolution in the performance of the deep learning methods over benchmark CDnet 2014 dataset.

The deep learning CD methods are further grouped into different types based on the characteristics such as dependence on hand-crafted background models, single/multiple frame-based segmentation, patch-based analysis, dependence on pretrained weights and finetuning. The generative adversarial networks (GANs) and autoencoders are another class of models used for CD. In terms of the experimental setups, the traditional and supervised methods require different considerations. The traditional methods for CD usually do not have prior requirement of labelled data for algorithms development. Thus, there is no need to define train-test splits. However, it is a crucial decision in supervised change detection techniques. The benchmark CDnet 2014 [34] and other datasets such as PTIS [35], and LASIESTA do not define the train-test division. Thus, researchers have used different data division strategies for network training and evaluation. We further categorize the supervised methods into scene dependent (SDE) and scene independent evaluation (SIE) setup. In ‘scene dependent’ setup, train and test sets consist of frames from the same video sequences. Whereas in ‘scene independent’ setup, completely unseen videos are used for testing. A sample data-division strategy for SDE and SIE is shown in Fig. 3.

A. Challenges and Issues

There are many real-world challenges to robust CD such as background noise, intermittent object motion, foreground scale variation, illumination changes, and extreme weather conditions (refer to Fig. 6). The traditional methods [28], [28], [31], [31], [32], [32], [33], [51], [56], [57], [64], [88] address these diverse challenges by feature extraction, background modelling and thresholding to identify the changes accurately. These CD techniques do not require any labeled samples for algorithm development. These methods naturally follow scene independent strategy for performance evaluation. Thus, the evaluations across different CD datasets are uniform as all the labeled frames in the video are used for evaluation and
none of them are used as priors in the traditional algorithms. On the other hand, the supervised approaches require certain amount of labelled training data/samples in order to learn optimal model parameters. However, most of the existing CD datasets [34], [79] do not provide a clear demarcation for training and testing samples. This simple observation gives rise to the question, “what should be the data division strategy for supervised change detection?”. The researchers [19], [20], [66]–[71], [80], [89]–[92] have adopted different data division schemes to evaluate and compare their supervised models with existing methods. The supervised deep learning methods have dominantly shown very high performances over these datasets. However, these approaches most prominently used SDE strategy is to select training data from certain temporal proportions of video sequence. Since the background remains more or less similar in the entire video sequence, the train and test data are highly similar. In other words, most of the deep learning models [19], [20], [66]–[71], [80], [89]–[92] have been either optimized for one specific video or a group of similar videos. We denote such training and evaluation scheme as scene dependent evaluation (SDE). In SDE, some frames from the test videos are used for training the model. This would give an unfair advantage to the CNN model in evaluation in comparison to traditional unsupervised methods. This has led to bloated results over the benchmark datasets [34], [79]. The performance of the trained models has not been evaluated on unseen videos. The same warning is clearly mentioned in changedetection.net leaderboard page: “Methods with the “supervised method” tag involve a supervised machine learning algorithm potentially trained on the ground truth data used to produce the metrics reported in this page”.

Moreover, even for SDE setup, inconsistent data split strategies in different papers [19], [20], [66]–[71], [80], [89]–[92] has also led to documentation of incomparable results. There is a need for clearly defined data-division schemes for training and evaluation in SDE setup. Furthermore, to evaluate the robustness of deep learning models in completely unseen videos, it is important to ensure scene independence in the evaluation of supervised CD methods. We discuss and compare the training and evaluation frameworks of different deep CD methods in detail in Section III.

Another very challenging aspect is the model design of deep CD methods. Some important considerations are (i) how to initialize the background? (ii) how to model the background and/or the motion information? (iii) is support of traditional background subtraction algorithms needed? (iv) how to pre-process and post-process the input and output data respectively? (v) which datasets or a subset of the datasets are suitable for evaluation and what are their characteristics? A number of deep learning models have been proposed which attempt to answer some of these issues for various scenarios. Different methods handle the challenges differently. Most of the models use encoder-decoder blocks to generate the binary segmentation map representing the pixel-wise changes in the current frame. Furthermore, several post-processing steps are also used for computing the final response of the CD methods. We discuss and compare the model design and characteristics of different deep CD methods in detail in Section II.

TABLE I: Summarization of a number of related surveys in the last decade

| No. | Pub-Year | Title                                      | Content                                                                 |
|-----|----------|--------------------------------------------|------------------------------------------------------------------------|
| 1   | CSR-2014 | [38] Traditional and Recent Approaches in Background Modeling for Foreground Detection: An Overview | A survey of the traditional approaches for background subtraction        |
| 2   | CVIU-2014|[37] A Comprehensive Review of Background Subtraction Algorithms Evaluated with Synthetic and Real Videos | A detailed comparison of 29 background subtraction methods in terms of quantitative performance and computational complexity |
| 3   | TITS-2016| [38] A Survey of Viison-Based Traffic Monitoring of Road Intersections | A review of studies related to vehicle detection and tracking in intersection-like scenarios |
| 4   | WACV-2016|[39] A Survey on Moving Object Detection for Wide Area Motion Imagery | An overview of the existing methods for moving object detection in WAMI data |
| 5   | CVIU-2016| [40] Detection of Stationary Foreground Objects: A Survey | A survey of the most relevant approaches for detecting all kind of stationary foreground objects |
| 6   | TITS-2017| [41] Video Processing From Electro-Optical Sensors for Object Detection and Tracking in a Maritime Environment: A Survey | An overview of various approaches of video processing for object detection and tracking in the maritime environment |
| 7   | AIR-2017 | [42] Review of Background Subtraction Methods using Gaussian Mixture Model for Mideo Surveillance Systems | A review of various background subtraction algorithms based on GMM |
| 8   | PRL-2017 | [43] Scene Background Initialization: A Taxonomy | A taxonomy study for background initialization methods for background subtraction |
| 9   | TITS-2018| [44] Object Detection in a Maritime Environment: Performance Evaluation of Background Subtraction Methods | A benchmark of the performance of 23 existing background subtraction algorithms for maritime vision |
| 10  | Jol-2018 | [45] Background Subtraction for Moving Object Detection in RGB-D data: A Survey | A review on the background subtraction methods for moving object detection in RGB-D data |
| 11  | CSR-2018 | [46] New Trends on Moving Object Detection in Video Images Captured by a Moving Camera: A Survey | A survey on the existing moving object detection methods in video sequences captured by a moving camera |
| 12  | IA-2019  | [47] A Comprehensive Survey of Video Datasets for Background Subtraction | A comprehensive account of the available public datasets for change detection |
| 13  | NN-2020  | [48] Deep Neural Network Concepts for Background Subtraction: A Systematic Review and Comparative Evaluation | A survey of the background initialization and subtraction methods based on deep neural networks |
| 14  | Arxiv-2020| [49] Moving Objects Detection with a Moving Camera: A Comprehensive Review | A categorization of existing methods for moving object detection with a moving camera |
| 15  | TITS-2020| [50] Detection of Motorcycles in Urban Traffic Using Video Analysis: A Review | A review of the algorithms used for detection and tracking of motorcycles in CCTV cameras |
| 16  | Ours     | An Empirical Review of Deep Learning Frameworks for Change Detection: Model Design, Experimental Frameworks, Challenges and Research Needs | A comprehensive empirical review of the recent deep learning model designs (technical characteristics) and evaluation frameworks for change detection |
B. Comparison with Previous Reviews

Many notable surveys related to change detection have been published, as summarized in Table I. These include many excellent surveys of the traditional background subtraction methods [36], [37], [42], [45], [47], deep neural network methods for background subtraction [48], traffic monitoring [38], [50], background initialization [43], foreground detection [40], wide area motion detection [39], maritime surveillance [41], [44], and moving object detection with a moving camera [46], [49].

There are comparatively very few surveys focusing directly on the deep learning based methods for change detection. Bouwmans et al. [48] conducted a survey of the existing deep neural network based methods. The research only discusses about the categorization of different types of networks. Moreover, the authors assume a uniform evaluation setup among the existing methods while introducing the comparative performance evaluation tables. Specifically, it fails to address the two important issues related to the evaluation frameworks in the literature:

- The training-testing divisions in the existing deep change detection methods are different to each other. The inconsistent data-division strategies make the results in claimed by different papers incomparable to other approaches.
- The frames from the same video are used in both training and testing set, giving the models unfair advantage while testing. Recently, few researchers [72], [74], [86] have addressed this issue by presenting scene independent evaluation (SIE) in completely unseen videos.

The survey in [48] does not present the comparative view of the different type of evaluation strategies adopted in the existing deep learning methods. In contrast, a thorough empirical review of the existing deep learning model designs (technical characteristics) along with the evaluation frameworks is presented in our survey. To the best of our knowledge, this is a first attempt to comparatively analyze the different evaluation frameworks adopted in the existing deep change detection methods.

C. Contributions and Organization of this Review

Motivated by the objectives discussed in the previous sections, this paper divides the CD methods into broad categories and respective subcategories to provides a comprehensive review of most representative deep learning-based CD approaches. Our paper presents an empirical review and analysis of the existing deep CD methods in terms of design decisions, effects and best practices. Moreover, we point out some of the glaring oversight in most of the deep CD methods in terms of training and testing data division. We analyze these factors in detail and also discuss some of the possible solutions. The summary description of the large-scale CD datasets is provided. In addition, we discuss new trends in the community, and provide several interesting ideas for new methods. We hope to help readers gain valuable knowledge in deep CD algorithms and choose the most appropriate approach for
Fig. 5: The focus of this study is the recent deep learning CD methods. The milestones of the most representative deep learning frameworks and datasets [20], [34], [66]–[69], [71]–[87] are shown here.

their specific applications. We first group the CD methods in terms of algorithm characteristics. We also group the existing methods in terms of the evaluation frameworks. We summarize our contributions as follows: (i) As shown in Fig. 7, a detailed categorization of existing approaches is provided in change detection. We classify the methods into two categories. Then, for each category, different subcategories are further defined. (ii) We provide a detailed discussion and overview of the technical characteristics of the different methods in supervised deep CD methods (refer to Table II and Table III). (iii) We categorize the training and evaluation frameworks adopted by the supervised methods in related video datasets (refer to Table IV and Table V). After careful analysis, we identify the shortcomings in the widely adopted setup and provide directions for fair comparative analysis. We also discuss the future direction and research opportunities in Section V. We conclude our work in Section VI.

II. DEEP LEARNING MODELS FOR CHANGE DETECTION

The chronological advancement in the change detection algorithms is depicted in Fig. 4. The focus of this study is highlighted in colored background. Further, in Fig. 5, we present the milestone deep learning algorithms and datasets for change detection. We present an empirical study of these deep learning methods. As shown in Fig. 7, the CD methods can be grouped into traditional and deep learning-based methods. We first give a brief overview of the traditional methods. We then characterize the deep learning methods with properties such as pretrained Weights and finetuning, diverse network input, auxiliary blocks & Layers, supervised and semi-supervised methods. The different methods are discussed in terms of the model design and other technical characteristics.

Fig. 6: Visual depiction of some of the challenges in change detection

A. Traditional CD Methods

The general framework for traditional change detection techniques can be roughly divided into three stages: feature extraction, background model initialization and maintenance, and foreground detection.

1) Feature extraction: The low-level image features, i.e., grayscale/color intensity [25]–[28], [33], [57], [59], [64], [93], [94] and edge magnitudes [95], [96] are commonly used in change detection algorithms. Superpixel based features have also been used in [97]–[99]. Moreover, specific spatial and
spatiotemporal feature descriptors [31], [32], [88] have been designed for enhanced performance.

2) Background model initialization and maintenance: The background modelling techniques can be loosely categorized into parametric [25]–[27], [100]–[103], non-parametric [28], [28], [31], [31], [32], [32], [33], [51], [56], [57], [64], [88], traditional learning-based [30], [58], [60], [104]–[116], hybrid [62], [63], [94], [117] and other [118]–[120] approaches.

Parametric approaches. In parametric approaches, the distribution at each location is modeled and updated through statistical models such as mixture of Gaussians (MOG) [26] and Expectation Maximization (EM) algorithms. Zivkovic [25] and Varadarajan et al. [27] improved upon the MOG with variable parameter selection, spatial mixture of Gaussians and fast initialization. Similarly, extension of these models [101], [102] and other statistical models were also developed in literature such as Poisson distribution [121], Dirichlet distribution [100] and regression models [103].

Non parametric approaches. The non-parametric methods are primarily inspired by the strategies based on kernel density estimation [56] and the consensus-based method [51]. In a seminal work ViBe [57], three significant background model maintenance policies were proposed: random background sample replacement to represent short and long-term history memoryless update policy and spatial diffusion via background sample propagation. These strategies have been widely adopted in recent state-of-the-art change detection techniques [29], [31]–[33], [88]. Adaptive update policies for decision thresholds (for foreground segmentation) and learning rates (for model update) were introduced in [33]. Furthermore, adaptive feedback mechanism to continuously monitor background model fidelity and segmentation entropy to update these parameters were presented in [28], [31], [32]. Mandal et al. [64] proposed a deterministic policy to update background models.

Traditional learning based approaches. Numerous learning-based techniques such as neural networks (NN), support vector machines (SVM) and principal component analysis (PCA) have also been presented in the literature. The seminal work in NN called self-organizing background subtraction (SOBS) [104], [105] was based on a 2d self-organizing neural network architecture. The network builds the image sequence neural background model by learning in a self-organizing manner, preserving pixel spatial relations. It behaves as a competitive neural network by implementing a winner-take-all function and a mechanism that updates the local weights of neurons, allowing learning to be spatially restricted to the local neighborhood of the most active neurons. Several improvements over these models have also been documented in [30], [106], [107].

SVM models [109]–[111] have been used at different stages in background subtraction. Cheng and Gong [109] generalized the one class support vector machines (1-SVMs) to accommodate spatial interactions to support online learning framework to track temporal changes over time. Similarly, Han and Davis [110] estimated the background likelihood vectors for a set of features and performed background subtraction using an SVM. Similarly, others [111] have also explored the SVM models for change detection.

The PCA has been exploited for subspace learning to handle illumination changes in the video sequences. Earlier methods used the discriminative [112], [113] and mixed [114] subspace learning models. However, the regular subspace models suffer from high sensitivity to noise, outliers and missing data. To alleviate these issues, robust principal component analysis (RPCA) based models [60], [65], [122], [123] have been designed to estimate background as a low-rank component and foreground as a sparse matrix. Robust spatiotemporal subspace modelling for dynamic videos were presented in [122], [123]. Many other incremental works are also presented to improve performance with PCA models in [58], [115], [116], [124].

Hybrid approaches. Many works [62], [63], [94], [117] have combined different modalities of algorithms to improve the performance. Bianco et al. [62] conducted multiple experiments to combine various change detection techniques through genetic programming. Sajid et al. [94] proposed to use multiple background models and fusion of RGB and
YCbCr color models to estimate the background probability. Similarly, semantic segmentation [63] inclusion are some other interesting hybrids presented by the researchers.

**Other approaches.** Many other non-conventional approaches have also been successful in performing background subtraction. Local codebook-based models [118], motion modeling using graph cut and optical flow [125], edge-based foreground segmentation [126] and physics-based change detection [119] are some other interesting methods proposed by the researchers to solve the problems in motion detection. Similarly, fuzzy models [120] have also been explored in the literature. A more detailed categorization of traditional change detection techniques can be found in [36].

3) Foreground detection: Threshold based segmentation with post-processing techniques [51], [57], [63], [94] are commonly used in the existing literature for foreground detection. Numerous policies [28], [32], [33], [64], [118] have also been proposed to adaptively update the foreground segmentation thresholds. Moreover, fuzzy similarity between background model and current frame has been measured through interval similarity and membership values in [120].

### B. Deep Learning based Methods

Deep learning techniques have achieved superior performance as compared to the traditional hand-crafted approaches in various computer vision tasks including image classification, object detection, semantic segmentation, visual object tracking, action recognition, etc. [3], [16], [17], [128]–[135]. Recently, many researchers have used the convolutional neural network (CNN) to segment the video frames into foreground and background regions, i.e. change detection. The challenges in designing CNN models for CD is much different from other image and video-based problems. For example, in image classification, object detection and semantic segmentation, the features are learned only in the spatial domain. The features in the spatial dimension are sufficient for such single image-based decision-making problems. These tasks do not require attention to the features in temporal dimension. Therefore, the models designed for these tasks do not work directly in CD. Similarly, in action recognition, the features extracted from both spatial and temporal dimensions lead to prediction of high-level classification labels. However, CD demands spatiotemporal feature learning framework as well as low-level dense pixel-wise labels prediction. All, these factors make design and development of deep learning models for CD a very challenging task. We discuss the recent deep CD methods in terms of the following characteristics.

1) **Pretraining and Finetuning:** To take advantage of the foundational CNN architectures trained over large-scale image datasets, several studies have proposed the use of pretrained blocks or layers to enhance the representation capability of the CD models. The feature learning capability of off-the-shelf CNN models such as VGG16, ResNet50, and GoogleNet. Zeng et al. [90] proposed a novel multiscale fully convolutional network architecture which builds upon the VGG16 model. The features from different layers of the VGG16 are fused with the decoder layer to enhance the encoder-decoder for change detection [71], [83], [84], [89]–[91], [136], [137], [139], [140]. Ou et al. [138] designed the CD network with ResNet18 and encoder–decoder structure in order to retain the low-level features through a shallow architecture. Tao et al. [141] present a deep features fusion network based foreground segmentation method. The DFFNetSeg [141] network uses both shallow layers and deep layers of a deep semantic experiments with a variety of pretrained models including VGG16, ResNet50, and GoogleNet. Zeng et al. [90] proposed a novel multiscale fully convolutional network architecture which builds upon the VGG16 model. The features from different layers of the VGG16 are fused with the decoder layer to enhance the encoder-decoder for change detection [71], [83], [84], [89]–[91], [136], [137], [139], [140]. Ou et al. [138] designed the CD network with ResNet18 and encoder–decoder structure in order to retain the low-level features through a shallow architecture. Tao et al. [141] present a deep features fusion network based foreground segmentation method. The DFFNetSeg [141] network uses both shallow layers and deep layers of a deep semantic
segmentation network PSPNet. In [81], a multi-branch network consisting of a recurrent branch and semantic branch was presented. The semantic branch uses a DeepLabV3+ model for semantic prediction. Similarly, Tezcan et al. [74] used the DeepLabV3+ to produce semantic segmentation outcome of each frame to obtain semantically accurate foreground detections. Mandal et al. [12] utilize the ResNet50 backbone to train a bounding-box based detector to localize and classify only the moving objects in a video.

2) Diverse Network Input: The traditional practices either create a parametric model [25]–[27] of the background with few past frames or develop a non-parametric background model [31], [32], [64] based on the recent 20-30 frames. The input layer to a deep learning model is defined in the network design phase. The trained model expects the input in a particular shape to compute the final output. The existing deep learning CD methods have employed diverse network inputs to train the models. We can categorize them into networks with: single frame [67], [69], [71], [82]–[84], [90], [138]–[140], [143]–[145], 2 frames [66], [68], [70], [85], [87], [89], [92], [136], [149]–[156], 3-10 frames [20], [72], [80], [91], [141], [157], [158], 11-30 frames [81], [86], [137], [142], [159]–[161], and 50 frames [19], [72]. The methods with single frame input primarily rely on the availability of certain labeled frames in a video. The model learns the presence of foreground pixels by training a single image based binary segmentation network. Lim et al. [71], [84] have designed multi-scale CNN architecture with single-frame input. Patil et al. [146] feed a pre-processed frame to the encoder-decoder. Similarly, others [67], [69], [82], [83], [90], [138]–[140], [143]–[145], [147], [148] have also pursued such approaches.

We depict the difference between the training process in single frame and multiple frames based input for change detection in Fig. 10. The methods with 2 frames as input aims to detect the changing pixels between them. Usually, these methods [66], [68], [70], [85], [87], [89], [92], [136], [139]–[156] first compute a background with the help of a traditional background subtraction method. Thereafter, the current frame and the background image is fed to the network to produce the result. Such inputs help the network learn the contrasting features for foreground segmentation. The methods with 3-10 frames combine multiple information from the current frame, previous frames, and the background frame. Yang et al. [80] temporally encoded the motion information by sampling multiple images from previous frames with increasing intervals. They also designed the network using atrous convolutions, skip connections and conditional random field (CRF) layers. Akilan et al. [20], [157] feed a 3-channel input (2-consecutive frames and a precomputed generic background) to their network. Some researchers have also used 11-30 frames as input to the network. Mongejar et al. [86] used 16 previous frames from a scene to generate a multidimensional map to represent the background model. Yang et al. [137] selected 14 frames to be fed to their spatio-temporal model. Mandal et al. [12] have conducted experiments with 10, 20, 30 frames as input to the network. Furthermore, methods [81], [159]–[161] have selected 12, 16, and 20 reference frames as well. Certain methods [19], [72] have also used 50 previous frames to model the background in and end-to-end manner for effective change detection.

Some methods have also partitioned the frames into patches and use it as input layer to the network [66], [68], [92], [152], [162]. Babaee et al. [68] first generate a background image using SuBSENSE and partition both the current frame and background into small patches and concatenated together to form the input layer. The motion features are learned by training a CNN network. The final response is generated by augmenting these segmentation maps. Nguyen et al. [92] process the smaller patches through a triplet CNN network to extract the relevant features for change detection. Similarly, the methods in [66], [67], [152], [162] also train the models in patch-based manner. In Fig. 11 we depict a representative existing method [66] that follow patch-level analysis.

3) Auxiliary blocks and layers: Several deep learning methods employ the statistical and hand-crafted background modelling techniques for temporal feature encoding. The reference background image is used along with the current frame for change detection. Similarly, some studies have proposed the addition of well-designed auxiliary blocks or layers to enhance the motion-related representation capability of the network. The following statistical auxiliary blocks have been used in the literature: SuBSENSE [68], [89], [92], [139], [144], IUTIS [66], [152], PAWCS [83], designed algorithm [91].
| Pub-Yr   | Input frames | Handcrafted support | Network type          | End-to-End | Pretrained weights | System config. | Speed | Evaluation setup |
|---------|--------------|---------------------|-----------------------|------------|-------------------|----------------|-------|------------------|
| ICSSIP-16 [66] | 2 frames, patch based | IUTIS-5 | CNN | No | No | NA | NA | SDE |
| ICME-17 [143] | single image | No | CNN, Multi-task Loss | Yes, DeepLab | Titan X | 5 fps | SDE |
| PRL-17 [67] | single image patch based | No | CNN | No | No | NA | NA | SDE |
| TCSVT-17 [69] | single image | No | CNN, ConvLSTM, CRF | Yes | ResNet50, VGG16, GoogleNet | Titan X | 5 fps | SDE |
| AVSS-17 [91] | 3 frames | Designed | CNN | Yes | VGG16 | NA | NA | SIE |
| IA-18 [63] | single image | PAWCS | CNN, Multi-scale | No | VGG16 | Titan Xp | 20 fps | SDE |
| Arxiv-18 [149] | 2 frames | No | Siamese Network, CNN | Yes | No | NA | NA | SIE, SDE |
| ICIP-18 [150] | 2 frames | No | CNN, MatchNet | Yes | No | NA | NA | SDE |
| ICME-18 [144] | single image | SuBSENSE | CNN, Multi-scale | No | No | GTX 1080Ti | 28 fps | SDE |
| ICME-18 [145] | single image | Random perm. of temporal pixels | CNN | No | No | NA | NA | SDE |
| ECCVW-18 [152] | 2 frames | No | CNN, Siamese Network | Yes | No | NA | NA | SDE |
| ICP-R-18 [82] | single image | No | LSTM, CNN | Yes | No | NA | NA | SDE |
| ACCV-18 [81] | 20 frames | No | LSTM, CNN | No | DeepLabv3+ | NA | NA | SIE, SDE |
| MWSCAS-18 [157] | 3 frames | temporal median | CNN, LSTM, skip connection | No | No | GTX 1080Ti | 45 fps, 15fps | SDE |
| IA-18 [159] | 12 frames | No | 3d CNN, ConvLSTM, atrous convolution | No | No | NA | NA | SDE |
| MTAP-18 [158] | 10 frames | No | 3d CNN | Yes | No | NA | NA | SDE |
| Sensors-18 [160] | 16 frames | No | 3d CNN, atrous convolution | Yes | Sports-1M | Titan Xp | 12 fps | SDE |
| IGRSL-18 [161] | 16 frames | No | 3d CNN | Yes | Sports-1M | NA | NA | SDE |
| ICI-18 [159] | 2 frames | SubSENSE | CNN, skip connection | No | VGG16 | GTX 1080Ti | 48 fps | SIE |
| PRL-18 [71] | single image | No | CNN, multi-scale | Yes | VGG16 | GTX 970 | 18 fps | SDE |
| IGRSL-18 [90] | single image | No | CNN, skip connection | Yes | VGG16 | GTX 1060 | 27 fps | SDE |
| TCSVT-18 [82] | 2 frames, patch based | SubSENSE | CNN | No | No | NA | NA | SDE |
| PR-18 [68] | 2 frames, patch based | SubSENSE | CNN | No | No | NA | NA | SDE |
| SMC-18 [146] | single image | temporal saliency map | CNN, multi-scale | No | No | GTX 1080 | 10 fps | SDE |
| TITS-18 [80] | 6 frames | No | CNN, CRF, skip connection atrous convolution | Yes | No | NA | NA | SDE |
| TITS-18 [19] | 50 frames | No | CNN | Yes | No | NA | NA | SDE |
| ICP-R-18 [70] | 2 frames | temporal median | GAN | No | No | GTX 1080 | 400 fps | SDE |
| PRCM-18 [152] | 2 frames, patch-based | IUTIS-5 | CNN, multi-scale | No | No | NA | NA | SDE |

TABLE II: Network design based comparison of the existing deep learning approaches. Year 2016-2018

Nguyen et al. [92] generated the background image using proven hand-crafted approaches SubSENSE. The SubSENSE background estimation (BE) block has also been used in [68], [89], [139], [144]. Similarly, other proven methods such as IUTIS [66], [152] and PAWCS [83] have also been added as the BE block. Fig. [12a] shows an existing method [71] using SuBSENSE as a BE block. Zhao et al. [145] designed a RPoTP block to capture the random permutation of temporal feature in a particular pixel. The historical observations at each pixel are permuted at random. The RPoTP feature map is subtracted from the current frame for subsequent processing by the CNN model. Lim et al. [91] and Tao et al. [141] have also augmented designed blocks to encode the historical patterns. The temporal median has been quite frequently used as a simple temporal feature encoder in [70], [72], [74], [85], [87], [153], [156], [157], temporal histogram and motion saliency map [73], [146], [163], optical flow [127], [155], [164], [165], and conditional random fields (CRF) [67], [69].

4) Supervised methods: The most commonly adopted framework for deep learning-based CD is the supervised setup. The methods use the manually labeled ground truths from the respective datasets for model training. The existing deep supervised CD methods can be categorized according to the following technical characteristics:

2D-CNN. Most of the existing deep CD methods in the
| Pub-Yr | Input frames | Handcrafted support | Network type | End-to-End | Pretrained weights | System config. | Speed | Evaluation setup |
|--------|--------------|---------------------|--------------|------------|-------------------|----------------|-------|-----------------|
| IA-19  | 15 frames   | patch-based         | LSTM, CNN    | No         | No                | Titan Xp       | 36 fps| SDE             |
|        |              |                     |              |            |                   |                |       |                 |
| IA-19  | 2 frames    | No                  | CNN, multi-scale | Yes       | VGG16             | GTX 1080Ti    | 22 fps| SDE             |
|        |              |                     |              |            |                   |                |       |                 |
| IA-19  | 14 frames   | No                  | ConvLSTM, CNN, multi-scale | Yes       | VGG16             | GTX 1080Ti    | 11 fps| SDE             |
|        |              |                     |              |            |                   |                |       |                 |
| IA-19  | single image | No                  | CNN, residual | ResNet18   | NA                | NA            | NA    | SDE             |
|        |              |                     | CNN, skip connections | Yes       |                   |                |       |                 |
| JIEI-19| single image | SuBSENSE, FTSG, CwisarDH | Yes    | Yes       | VGG16             | NA            | NA    | SDE             |
|        |              |                     | CNN, skip connections | Yes       |                   |                |       |                 |
| TVT-19 | 2 frames    | temporal median     | CNN, inception, residual | Yes       | GTX 1080Ti       | 42 fps        | SDE   |                 |
|        |              |                     |              |            |                   |                |       |                 |
| ISIE-19| single image | No                  | GAN, CNN ResNet, RoI Detection | Yes       | Yes               | NA            | NA    | SDE             |
|        |              |                     |              |            |                   |                |       |                 |
| W ACV-19| single image | temporal histogram | GAN          | No         | No                | NA            | NA    | SDE             |
|        |              |                     |              |            |                   |                |       |                 |
| BMVC-19| 16 frames   | No                  | CNN, U-Net   | Yes        | No                | NA            | NA    | SIE             |
|        |              |                     |              |            |                   |                |       |                 |
| TTTS-19| 4 frames    | No                  | 3D CNN, LSTM | Yes        | No                | GTX 1080Ti    | 24 fps| SDE             |
|        |              |                     |              |            |                   |                |       |                 |
| TVT-19 | single image | No                  | VGG16        | No         | GTX 1080Ti       | 134 fps       | SDE   |                 |
|        |              |                     |              |            |                   |                |       |                 |
| ISIE-19| single image | No                  | CNN, motion saliency map | Yes       | No                | NA            | NA    | SDE             |
|        |              |                     |              |            |                   |                |       |                 |
| AVSS-19| 3 frames    | designed algorithm  | CNN          | No         | PSPNet            | NA            | NA    | SDE             |
|        |              |                     |              |            |                   |                |       |                 |
| AVSS-19| 2 frames    | temporal median     | CNN, skip connection | No        | No                | GTX 1080Ti    | 134 fps| SDE             |
|        |              |                     |              |            |                   |                |       |                 |
| ISIE-19| single image | No                  | VGG16        | No         | GTX 1080Ti       | 33 fps        | SIE   |                 |
|        |              |                     |              |            |                   |                |       |                 |
| Sensors-19 | 2 frames | temporal median | CNN, Optical Flow | Yes        | No                | RTX 2080Ti   | 11 fps| SDE             |
|        |              |                     |              |            |                   |                |       |                 |
| ISIE-19| single image | Optical Flow        | CNN, Attention | Yes       | No                | Titan Xp      | 33 fps| SIE             |
|        |              |                     |              |            |                   |                |       |                 |
| Neuro-19| 2 frames    | temporal median     | GAN          | No         | No                | GTX 970       | 23 fps| SDE             |
|        |              |                     |              |            |                   |                |       |                 |
| Neuro-19| 2 frames    | temporal median     | GAN          | No         | No                | GTX 970       | 23 fps| SDE             |
|        |              |                     |              |            |                   |                |       |                 |
| W ACV-20| 10/20/30 frames | No                  | CNN, bounding box regression | Yes       | ResNet50          | Titan Xp      | 5 fps  | SIE             |

**TABLE III: Network design based comparison of the existing deep learning approaches. Year 2019-2020**

The literature have designed 2D-CNN models [19], [66]–[69], [71], [74], [80]–[87], [89]–[92], [136]–[147], [149]–[153], [155] to map the motion information. Learning the spatiotemporal features directly with 2D convolutional kernels is a non-trivial problem. Therefore, the researchers have designed additional blocks and layers (discussed in Section II-B3) to produce the contrasting effect for robust change detection. Patil et al. [19] have created average pooling layer in temporal direction (compatible in 2D-CNN network) to enable end-to-end operation without dependence on auxiliary modules. Using the 2D-CNN architecture also facilitate taking advantage of transfer learning with the pretrained weights (discussed in Section II-B1). The general design for all the existing methods resemble the encoder-decoder network structure as shown in Fig. 8. Some existing methods using 2D-CNN are depicted in Fig. 9a, Fig. 9b, Fig. 12 and Fig. 11.

**3D-CNN.** Studies in [20], [72], [158]–[161] show that performing 3D convolutions is a rewarding approach to capture both spatial and temporal dimensional features in videos. The effectiveness of 3D-CNN for change detection was first presented in [159]. A more robust model validated over completely unseen videos was presented in [72]. The authors designed 3DFR (refer Fig. 9c) to learn the spatiotemporal features through a swift feature reductionist approach in an end-to-end manner. Akilan et al. [20] used the 3D convolutions (refer Fig. 13b) to capture the short temporal motions while using LSTM to capture the long-short term temporal motions. Similarly, other 3D CNN network designs [158], [160], [161] have also been explored in the literature.

**Multi-scale features.** Multi-scale feature representations have been successfully used in semantic segmentation applications to achieve robust performance [133], [167]–[169]. Numerous CD approaches have also utilized multi-scale features (refer Fig. 9g) in the network [71], [72], [83], [136], [137], [144], [146], [147], [152]. Lim et al. [71] designed a triplet CNN that operates in three different scales for feature encoding. Mandal et al. [72] encode features from multiple 3D receptive fields \( T \times 1 \times 1 \), \( T \times 3 \times 3 \) and \( T \times 5 \times 5 \) (\( T \) denoting the kernel depth) and then take the average of the feature maps. Yang et al. [137] improve the robustness...
of background subtraction with an end-to-end multi-scale spatiotemporal (MS-ST) method. Likewise, the multi-scale features have been successfully employed in \cite{83,136,144,146,147,152}.

**ConvLSTM module.** To exploit the pixel-level temporal context, the change detection can be considered as a sequence labeling problem. Chen et al. \cite{69} proposed an attention ConvLSTM to model temporal changes over time. Similarly, Choo et al. \cite{81,82} and Yang et al. \cite{137} used a multi-scale ConvLSTM structure to model various types of spatial and temporal changes. Akilan et al. \cite{20} incorporate the cues from the LSTM module with the 3D-CNN network to robustly detect the moving objects. Some other notable works \cite{159,162} also include such modules in their network.

**Skip and Residual connections.** Usually, the first few layers consist of the low-level features as compared to the abstract high-level features at the deeper layers in the CNN network. The skip and residual connections help in preserving the detailed low-level features which contributes to more accurate pixel-wise binary segmentation at the final layer. Therefore several methods \cite{74,80,84,85,87,89–91,136,138,139,153,154,157} have used skip and residual connections in the network to obtain better performance (refer Fig. 9b, Fig. 12, and Fig. 13). In \cite{74,136}, the U-net \cite{170} structure has been adopted to benefit from same-level connections between the encoder and decoder. Lin et al. \cite{89} insert two residual connections at different scales between the encoder and decoder. Lim et al. \cite{91} add one single skip connection to concatenate the encoder and decoder layers for a particular resolution level. Akilan et al. \cite{153} design the network MvRF-CNN by introducing a large number of skip and residual connections. Similarly, the residual features are added at multiple stages of the network in \cite{87,90,138,139}. The atrous convolutions and attention based modules have also been implemented to improve the network capability for robust change detection \cite{80,155,159,159,160}.

**End-to-end vs Ensemble methods.** The change detection methods can also be categorized into end-to-end or ensemble methods. End-to-end implies that the CNN network takes the raw data as input and gives the final response without any support from external modules or blocks. The ensemble methods require a lot of intermediate computations leading to additional complexity. For example, Mandal et al. \cite{72} present 3DFR (Fig. 9c) that only use the previous 50 raw frames to compute the final segmentation map in an end-to-end manner. On the other hand, the Tezcan et al. \cite{74} aggregates a CNN, a semantic segmentation model, and temporal median to collectively perform change detection. The approaches in \cite{19,20,69,71,72,80,82,84,86,87,90,91,136,137,139,140,142,147,149,151,153–155,158,160} offer end-to-end solutions. Whereas, the methods in \cite{66–68,70,74,81,83,85,89,92}.
[41], [143]–[146], [148], [152], [156], [157], [159], [162]–[164] present a variety of assembled algorithms.

5) Semi-supervised Methods: With the advancements in generative adversarial networks (GAN) and autoencoders (AE), there has been a rise in the development of semi-supervised methods for change detection. The existing CD methods can be discussed in the following two groups:

GAN Based Methods. BakKay et al. [70] were the first to present a GAN based solution for background subtraction. They proposed a deep background subtraction model called BScGAN, using conditional GAN [171]. A simple U-net architecture with skip connections is used as a generator. The discriminator is composed of 4 convolutional and downsampling layers. Patil et al. [73] proposed an unpaired learning based approach FgGAN for background estimation and foreground segmentation. The FgGAN is inspired by the cycle-consistent adversarial networks (CycleGAN) [172]. The block diagram for FgGAN is shown in Fig. [14a] Zheng et al. [156] designed a background subtraction method based on parallel vision and Bayesian GANs. Sultana et al. [164] introduced an unsupervised algorithm by unifying an optical flow based pre-processor, GAN network for arbitrary region inpainting, Poisson blending based post-processor, and threshold based foreground detector. The detailed methodology is depicted in Fig. [14b]. Yu et al. [173] combined GAN with domain adaptation for background subtraction in remote sensing videos. Ammar et al. [174] utilize an anomaly discovery framework DeepSphere and GAN to segment and classify moving objects in video sequences.

Autoencoders Based Methods. Gracewell and John [148] designed an autoencoder network for background modelling. The network is first initialized with greedy layer wise pre-training approach and then fine tuned using conjugate gradient based back propagation algorithm. Garcia et al. [175], [176] proposed a CD system with a stacked denoising autoencoder extracting the salient features for each patch of several shifted tilings of the video frame. For each patch of the frame, a probabilistic model is learned that are considered in pixel-level classification. The autoencoders have also been used for background estimation [177]–[179] which can be used to further detect motion pixels.

III. TRAINING AND EVALUATION FRAMEWORKS

The performance of any supervised method is affected primarily by two factors: 1) the model uncertainty i.e., the uncertainty about model architecture and parameters, 2) the evaluation setting i.e., the strictness in the data-division to validate the generalization strength of the model. The technical analysis of the model designs of different methods is already presented in the previous section. In this section, we focus on the training and evaluation setups adopted by the existing methods.

Based on the extensive literature study, we report that the existing supervised CD methods has been evaluated with a variety of different training-testing set selections. The traditional methods [28], [31], [32], [63], [64] for change detection usually do not require labeled training data. Thus, there is no need to define train-test splits. However, it is a crucial decision in supervised (deep learning) change detection techniques. Most of the benchmark datasets like CDnet 2014 [34], LASIESTA [79], SB12015 [78], Fish4Knowledge [180], GTFD [181], UCSD [182], and PITS [35] do not define the train-test division. Thus, researchers have used different data division strategies for network training and evaluation. This makes the results claimed in different papers incomparable to each other as well as with previous unsupervised (traditional) approaches. We categorize the evaluation strategies into scene dependent evaluation (SDE), scene independent evaluation (SIE), and cross-dataset evaluation (CDE) settings (refer Fig. 3). A comparative analysis of different evaluation schemes is tabulated in Table IV and Table V.

A. SDE

In SDE setup, usually a certain percentage of frames from a video is put into a training and the rest is used for testing as shown in Fig. 15. Most of the existing deep learning methods [19], [20], [66]–[71], [80], [89]–[92] follow SDE scheme for evaluation. In [66], [69], [70], 50% frames from each video are selected for training. Similarly, 90% and 70% frames were used to train CNN models in [80] and [20], respectively. Few researchers [19], [67], [68], [71], [73], [90], [92], [146] have selectively or randomly chosen the training frames. In [68], 5% of the frames were randomly chosen for training. Likewise, 50/200 frames are manually selected in [67], [71], [73]. Moreover, 150 and 100 training frames are randomly in [90] and [92], respectively. In the literature, two types of SDE setups have been adopted for training: video-wise optimization and video-group wise optimization. In video-wise optimization, the network is optimized for each video separately. Whereas, in video-group wise optimization, the network is optimized over a group of videos (usually, the complete dataset) and a single model is obtained. The difference between these two types of training strategies is depicted in Fig. 15(a) and Fig. 15(b). A detailed description of the scene dependent settings in the existing methods is tabulated in Table IV and Table V.

Since all frames of a video sequence have the same background representation which is learned during training. Such schemes clearly favor the CNN model while testing. Therefore, even though high performance has been claimed in the literature, it is very difficult to evaluate their robustness in unseen videos. The problem is with the adopted experimental framework and not necessarily with model design. The stricter evaluation is possible when completely unseen videos are tested as done in the SIE setup.

B. SIE

In SIE setup, the train and test sets consist of completely different videos. It ensures evaluation over videos with unseen background. In Fig. 15(c), a sample video-agnostic setting is shown for scene independent evaluation. To ensure complete scene independence, Mandal et al. [72] adopted a leave-one-video-out (LOVO) strategy. They leave out 1 video from each category of CDnet 2014 for testing and use the remaining
TABLE IV: Experimental Setting based comparison of the existing deep learning approaches. V-Opt: Video Optimized, SI: Scene Independence, VFs: Video frames, vids: Videos CD14: CDNet 2014 Year 2016-2018

| Pub-Yr | Training data selection | Testing data selection | V-Opt | SI | Dataset |
|--------|-------------------------|------------------------|-------|----|---------|
| ICSSIP-16 [66] | 50% of VFs | Remaining 50% of VFs | Yes | No | CD14 (23 vids) |
| ICME-17 [143] | 50% of VFs | Remaining 50% of VFs | Yes | No | CD14(all) |
| PRL-17 [67] | Selective 50/200 VFs | Complete dataset | Yes | No | CD14(all), SBM2015 (14 vids) |
| TCSVT-17 [69] | 20%/30%/40%/50% of VFs | Remaining 80%/70%/60%/50% of VFs | Yes | No | CD14 (all), LASIESTA (all) |
| AVSS-17 [91] | 39 vids | 10 unseen vids | Yes | Yes | CD14 (49 vids) |
| IA-18 [63] | Video-wise, Selective 200 frames | Complete dataset | Yes | No | CD14 (all), SBM-RGBD |
| Arxiv-18 [149] | Image-pairs selection | Self defined test set | No | Yes | CD14, PVC2015, VL-CMU-CD |
| ICIP-18 [150] | Video-wise, selective 500 frames | Complete dataset | Yes | No | CD14 (all) |
| ICME-18 [144] | Video-wise, selective 500 frames | Complete dataset | Yes | No | CD14(all) |
| ICME-18 [145] | Video-wise, selective 1/20/40 frames | Complete dataset | Yes | No | CD14 (all) |
| ECCVW-18 [151] | Image-pairs selection | Self defined test set | No | Yes | CD14 (all), PVC2015, VL-CMU-CD |
| IICPR-18 [82] | Video-wise, selective 200 frames | Complete dataset | Yes | No | CD14 (all) |
| ACCV-18 [81] | Image synthesis, background frame | Complete dataset | Yes | No | CD14 (49 vids) |
| MWSCAS-18 [157] | 70% of VFs | Complete dataset | Yes | No | CD14 (7 vids) |
| IA-18 [159] | 80% of VFs | Remaining 20% of VFs | Yes | No | CD14 (all) |
| MTAP-18 [158] | 70% of VFs | Remaining 30% of VFs | No | No | CD14 (all), ESI (5 vids) |
| Sensors-18 [160] | 50% of VFs | Remaining 50% of VFs | Yes | No | CD14 (all) |
| IGRSL-18 [161] | 50% of VFs | Remaining 50% of VFs | Yes | No | CD14 (5 vids) |
| ICMP-18 [89] | 20 vids | 6 unseen vids | No | Yes | CD14 (26 vids) |
| PRL-18 [71] | Selective 50/200 VFs | Complete dataset | Yes | No | CD14 (all) |
| IGRSL-18 [90] | Randomly selected 150 VFs | Complete dataset | Yes | No | CD14 (5 vids) |
| TCSVT-18 [92] | Randomly selected 100 VFs | Complete dataset | Yes | No | CD14 (6 vids), BMC (5 vids), Wallflower (4 vids) |
| PR-18 [68] | Randomly selected 5% of VFs | Remaining 95% of VFs | Yes | No | CD14 (all), Wallflower (7 vids) |
| SMC-18 [146] | Randomly selected 5,500 frames of VFs | Remaining VFs | No | No | CD14 (35 vids), Wallflower (6 vids) |
| TITS-18 [80] | 90% of VFs | Remaining 10% of VFs | Yes | No | CD14 (6 vids) |
| TITS-18 [19] | Randomly selected 9,800 frames | Remaining VFs | No | No | CD14 (all), PTIS(all), LASIESTA (all) |
| ICIP-18 [70] | 50% of VFs | Remaining 50% of VFs | Yes | No | CD14 (49 vids), BMC (10 vids) |
| PRCM-18 [152] | 5/10/20 VFs | Remaining VFs | Yes | No | CD14 (49 vids) |

Fig. 15: The different training-testing data-division strategies adopted in the literature for deep CD methods. (a) video wise optimization, (b) video-group wise optimization, (c) video agnostic

for training and the remaining one video is used for testing. Such an experimental setup makes the model design much more challenging as compared to the SDE setup. Tezcan et al. [74] first collect all the videos across the categories into a single pool. Thereafter, they create 18 different subdivisions to ensure that the none of the training videos overlap with testing videos. This way, all the videos were at some point tested in completely unseen manner. Similarly, Mondezar et al. [86] conducted scene-wise 3-fold cross-validation in order to evaluate the capability of the proposed architecture to extrapolate to unseen scenes. The authors in [89] have also attempted to conduct SIE with only a selected set of videos from CDnet 2014.

C. Cross-dataset

Another kind of SIE can be ensured by using the models trained over a particular dataset and test on a completely
different public dataset. Patil and Murala [19] used the model trained over the CDnet 2014+LASIESTA to test the videos in PTIS. Similarly, in [127], the trained model on CDnet 2014 thermal videos are evaluated over GTFD. Other types of video selection schemes could be explored in future along with solving the network design challenges for the same.

D. SIE Vs SDE

As discussed in Section III-B, the SDE setup leads to model optimization only for the same set of videos used in training. This is due to the fact that some frames from the test videos are used for training. Therefore, it is essential to evaluate the model over unseen or scene independent videos. This also makes the process of model design much more challenging in order to ensure robust performance even in real-world scenarios. Such SIE scheme ensures proper evaluation of the designed model as compared to SDE. Therefore, the recent works have opted for more challenging SIE setups model evaluation. Teczun et al. [74] have shown that some of the models [71], [84] claiming very high performance in SDE setup performed poorly when evaluated with SIE setup. More specifically, the original paper for FgSegNetv2 model [71] reports an overall F-score of 98.9 over CDnet 2014. However, when trained and evaluated in the SIE setup as in [74], it could only obtain 37.15 F-score. Therefore, the SDE based results are unreliable to validate the actual robustness of the deep learning models. More recent benchmark datasets for other video-based applications [183], [184] already ensure such scene independency in their evaluation schemes. Based on all these observations, our proposition is to give more importance to SIE or CDE over SDE for change detection model evaluation. We demonstrate the performance degradation of FgSegNetv2 in SIE setup in comparison to SDE in Fig. 16.

E. Discussion

As discussed in Section III-D, the SIE/CDE setup is much more challenging than the popularly used SDE setup. However, even for SDE evaluation, we notice a clear inconsistency among the schemes adopted in the literature [19], [20], [66]–[71], [80], [89]–[92] to report the results over CD datasets. For traditional unsupervised methods, the experimental setup is clearly defined which makes these results comparable without any bias issues. However, in deep learning methods, it is essential to maintain nonoverlapping (SIE/CDE) between the training and testing sets. Moreover, it is highly desired that the training and testing data should not be similar as in SDE. These factors have not been carefully considered in the existing literature. For example, although temporal information forms the basis of change detection, the highest results claimed in [71], [84] do not even consider it in their respective CNN models. They use a carefully selected set of frames (50/200 frames) from each video to train the model and achieve more than 98% F-score over CDnet 2014 dataset. It can be argued that such evaluation is clearly overfitted as the training and testing data is almost the same and no spatiotemporal feature is learned by the networks to identify the change. Such models are not suitable to handle the challenges in change detection in unseen videos as demonstrated through Fig. 16. Moreover, even for SDE setup, researchers have apparently adopted different SDE schemes for training and evaluation. These documented results cannot be fairly compared. Therefore, benchmarking the performances of different CNN, GAN models in a standard evaluation setup (SDE/SIE/CDE) is an important scope in change detection research.

IV. DATASETS AND EVALUATION METRICS

The current research needs across all the computer vision applications are motivated by the success of deep learning algorithms. The success of the deep learning algorithms depends on the availability of sufficient labeled training data that include as many variations of the populations and environments as possible. Higher the diversity in the captured video scenarios for training, the more robustly one can estimate the model parameters.

In this section, we primarily discuss about the publicly available change detection datasets that has been used for evaluating the deep learning methods in the literature. A more detailed review of all the existing datasets for CD is presented in [47]. We list out the most popular datasets used in the deep learning methods for evaluation in Table V. It provides the main reference, number of videos, number of frames, number of labels, and the access details. These are the most relevant information needed while working with deep learning methods. Sample video frames from some of these datasets are shown in Fig. 17. Below, we discuss these change detection datasets based on the type of captured video frames i.e. conventional, thermal, underwater, and aerial.

**Conventional video datasets:** The eight conventional CD datasets: CDnet 2014 [34], LASIESTA [79], PTIS/I2R [35], SBI2015 [78], UCSD [182], SegTrack-v2 [185], DAVIS-2016 [186], FBMS [187], have been most prominently used for evaluation in the literature. Among them, CDnet 2014 [34] offers the most diverse set of scenarios along with the highest number of labeled frames (90,000). The video sequences are
TABLE V: Experimental Setting based comparison of the existing deep learning approaches. V-Opt: Video Optimized, SI: Scene Independence, VFs: Video frames, vids: Videos CD14: CDNet 2014 Year 2019-2020

| Pub-Yr | Training data selection | Testing data selection | V-Opt | SI | Dataset |
|--------|--------------------------|------------------------|-------|----|---------|
| IA-19 [162] | Video-wise, selective frames | Complete dataset | Yes | No | CD14 (all) |
| IA-19 [136] | Video-wise, selective 50/200 frames | Complete dataset | Yes | No | CD14 (all) |
| IA-19 [137] | Video-wise, 70% of VFs | 30% of VFs | Yes | No | CD14 (all), LASIESTA |
| IA-19 [138] | Video-wise, random 20% selected frames | Complete dataset | Yes | No | CD14 (all), PTIS |
| JIE-19 [139] | Video-wise, randomly selected frames | Complete dataset | Yes | No | CD14 (all) |
| TITS-19 [140] | Video-wise, 70% of VFs | 30% of VFs | Yes | No | CD14 (16 vids) |
| TVT-19 [141] | Video-wise, 70% of VFs | 30% of VFs | Yes | No | CD14 (17 vids) |
| Neuro-19 [142] | NA | NA | NA | NA | CD14 (10 vids), AICD 2012, aerial dataset |
| ISIE-19 [140] | Video-wise, selective 50/200 frames | Complete dataset | Yes | No | CD14 (all) |
| WACV-19 [143] | 200 VFs | Remaining VFs | Yes | No | CD14 (38 vids) |
| BMVC-19 [86] | Scene-wise 3-fold cross-validation | Scene-wise 3-fold cross-validation | No | Yes | CD14 (49 vids) |
| TITS-19 [89] | 70% of VFs | Remaining 30% of VFs | Yes | No | CD14 (16 vids) |
| PAA-19 [94] | 25/200 VFs and 20%/50% of VFs | Remaining VFs, Remaining 80%/50% of VFs | Yes | No | CD14 (all), UCSD (18 vids), SBI2015 (14 vids) |
| AVSS-19 [163] | 1100 VFs | Remaining VFs | No | No | CD14 (100 vids), Fish4Knowledge (7 vids) |
| IA-19 [141] | 80% of VFs | Remaining 20% of VFs | Yes | No | CD14 (all), LASIESTA |
| AVSS-19 [147] | N% of VFs | N% of VFs | Yes | No | CD14 (28 vids) |
| AVSS-19 [149] | 160 VFs | 40 VFs | Yes | No | CD14 (all) |
| Sensors-19 [155] | Randomly selected 5% of VFs | Remaining 95% of VFs | No | No | CD14 (all), PETS2009, Wallflower (6 vids) |
| ISPL-19 [156] | 38 vids | 10 unseen vids | No | Yes | CD14 (48 vids) |
| MVA-19 [164] | Unsupervised approach, labeled data not required | Complete dataset | No | Yes | CD14 (35 vids) |
| Neuro-19 [156] | Randomly selected 100 VFs | Complete dataset | Yes | No | CD14 (all), UCSD (18 vids), SBI2015 (14 vids) |
| MTAP-19 [148] | Unsupervised approach, labeled data not required | Complete dataset | No | Yes | CD14 (49 vids), AVSS, CAVAR |
| WACV-20 [147] | 18 split-combinations of all the vids | 18 split-combinations of all the vids | No | Yes | CD14 (all) |
| WACV-20 [149] | 16 vids | 3 unseen vids | No | Yes | CD14 (19 vids) |

TABLE V: Experimental Setting based comparison of the existing deep learning approaches. V-Opt: Video Optimized, SI: Scene Independence, VFs: Video frames, vids: Videos CD14: CDNet 2014 Year 2019-2020

quite large with an average video length of about 3005 frames. Whereas, SegTrack-v2 [185], DAVIS-2016 [186], FBMS [187] provide small videos with average video lengths 70, 69, 234, respectively. The LASIESTA [79] provides the object category labels along with the foreground pixel labels. However, the dataset contains only three type of objects. The PTIS [35], SBI2015 [78] and UCSD [182] provides further challenging set of videos for change detection.

Underwater datasets: For moving object detection in underwater videos, the Fish4Knowledge [180] and UnderwaterCD [188] datasets have been introduced. The Fish4Knowledge [180] contains 17 videos each containing about 2777 frames. However, the labels for only a combined 869 frames are available for all the videos. The UnderwaterCD [188] has only 5 videos. Each video has 100 frames and 100 labels for evaluation.

Thermal video datasets: One of the categories in CDnet 2014 [34] consist of 5 thermal videos. Overall, there are 21,100 frames and 6,137 labels. Recently, more datasets are created for thermal video-based change detection. The GTFD [181] dataset introduced 25 new videos captured with infra-red devices. A total of 1,067 frames are available to analysis. The TU-VDN [189], [190] captured longer thermal video sequences (19 videos, 43,247 frames) from challenging scenarios for change detection.

Aerial video datasets: More recently, Mandal et al. [191] introduced a new large-scale aerial video dataset named MOR-UAV. The dataset consists of aerial videos captured from UAVs in numerous scenarios. The moving objects are labeled with axis-aligned bounding boxes along with corresponding object class. The bounding box labelling requires less computational resources than producing pixel-level estimates. Moreover, the associated foreground labels are useful in many applications.

A. Evaluation Metrics

Researchers have used a variety of metrics to measure the effectiveness of the change detection methods. However, identifying the best metric to accurately measure the potency of a change detection method is a non-trivial decision. The designed CD method must be able to report minimal false positive (FP) and false negative (FN). Similarly, the count for true positive (TP) and true negative (TN) should ideally
be on higher side. The precision favors methods with low FP whereas, the recall favors methods with low FN. Thus, the F-score presents a balanced metric which demands lower values of both FP and FN. Similarly, the Percentage of Wrong Classifications (PWC) computes the ratio between all the wrong classifications (FP+FN) by the total predictions (TP+TN+FN+FP). The mean absolute error (MAE), specificity, false positive rate (FPR), false negative rate (FNR), also offers useful insights about the ability of the CD methods. We define the performance metrics: precision, recall, specificity (Sp), FPR, FNR, F-score (FS), and PWC for pixel-wise change detection in Eq. [1] - Eq. [7]

\[
\text{Precision} = \frac{TP}{TP + FP} \quad (1) \quad \text{Recall} = \frac{TP}{TP + FN} \quad (2) \\
Sp = \frac{TN}{TN + FP} \quad (3) \quad FPR = \frac{FP}{FP + TN} \quad (4) \\
FNR = \frac{FN}{TN + FP} \quad (5) \quad FS = 2 \times \frac{Pr \times Re}{Pr + Re} \quad (6) \\
PWC = 100 \times \frac{FN + FP}{FN + FP + TP + TN} \quad (7)
\]

V. RESEARCH NEEDS AND FUTURE DIRECTIONS

A. Research Needs

1) Bench-marking the deep learning results: As discussed in Section [III-E] there is a problem of non-comparability among the recent deep learning-based change detection methods. Different CNN networks have been trained over different training-testing data-divisions. This is due to unavailability of earmarked divisions for train and test set in the large-scale datasets such as CDnet 2014, LASIESTA, and SBI2015. Some recent methods [74], [86] have evaluated the model with cross-data validation by testing over completely unseen videos. However, the ad-hoc nature of the cross-validation data divisions raise the question of data division bias in order to boost the performance of the proposed models. Similarly, the authors in [72] evaluate over selected unseen videos to show robustness of the models. There is a need for benchmark data division to ensure uniform comparative analysis of the presented deep learning models.

2) Change detection datasets: As discussed in the previous section, the labeled CD datasets are available for natural, thermal and underwater scenes. All these videos are captured with fixed cameras. Few datasets [33], [79] contain limited set of videos captured with moving cameras. However, the camera motion is very miniscule and under controlled settings. There is a need for labeled CD datasets captured with unconstrained camera movements. An example of unconstrained scenario is the videos captured with the dash camera inside a moving vehicle. Such a dataset could potentially pave the way for a new set of challenges for deep learning algorithms.

The aerial view-based CD is another important research area that requires specific attention. There is a need for labeled CD dataset for aerial videos captured from UAV mounted cameras. Some recent datasets [192]–[194] have presented annotations for object tracking and video object detection. Similarly, the CD labels could be produced for evaluation of change detection models in aerial scenes.

3) Robustness and Real-time Challenges: To attain robust performance in real-world scenarios, it is important to validate the models in SIE and CDE settings. Furthermore, the current reported model speeds (GPU or CPU) are not comparable due difference in the hardware configurations. There is a need to benchmark the process of measuring the speed of the deep learning models [22].

4) Bounding-box based motion detection: Most of the CD datasets provide pixel-wise labels which require algorithms to estimate pixel-wise binary classifications. The object class (car, person, truck, etc.) for the foreground pixels are not identified. Separate object detectors [195] could be used for obtaining the relevant object classes as post-processing. However, this will lead to poor latency, inefficient resource utilizations and memory overhead. The recent work in [12] advertise the utility of a single stage localization and classification algorithm for moving object recognition (MOR) in end-to-end manner. This work takes advantage of the state-of-the-art object detectors [195], [196] to achieve robust MOR performance. The authors annotate the CDnet 2014 for training the bounding-box based MOR algorithm. Further investigation in this direction should be done to benefit from the rapid advancement in deep learning-based object detectors.

B. Future Directions

1) CD in Aerial Videos: Aerial vision-based data is being generated in abundance in both consumer and industrial market space. The aerial video data captured with UAV-mounted cameras facilitate numerous applications such as aerial surveillance, search and rescue, event recognition, urban and rural scene understanding. Thus, change detection in aerial videos is an important domain of research. Some of the most challenging scenarios is to detect object motion when the camera mounted UAV is also moving either in same direction or in other direction of the moving objects [191], [197]. Similarly, the variable speed of objects and the UAVs lead to even more challenging cases. The future works should focus to address these challenges by both collecting labeled data and designing novel algorithms for aerial videos.

2) CD in Moving Cameras: There has been some important research in the field of CD from moving cameras [46], [198]. However, limited labeled datasets and lack of deep learning-based solutions make it a very important research direction to explore. Most of the existing CD work primarily focused on the fixed camera-based videos. The future work requires more attention towards both data collection and algorithm development in the direction of CD in moving cameras. The autonomous vehicles and aerial video analytics are two prominent applications for such solutions.

3) Vision-based Forecasting in Videos: The deep learning-based methods have bridged the gap between research and real-world applications for vision-based detection, recognition and segmentation. However, beyond these well studied problems, vision-based forecasting will likely be one of the next big research topics. The ability to make prediction the future in
videos will test the ability of the deep learning algorithms. The existing CD algorithms can be extended to predict the location of the moving objects in future frames. This will have utility in traffic monitoring [18], [38], anomaly detection [15], [17], trajectory prediction [199], [200], etc.

One of the applications of such algorithms can be autonomous driving [13], [132], where precognition of certain events, object positions, through vision-based understanding of the temporal video data can resolve some of the safety issues. The research could be dedicated towards future object localization and anticipation of trajectories. The existing CD datasets can be re-purposed to serve as benchmark to evaluate models to predict the future location of objects after few frames (10/20/30/40... frames).

4) Self-supervised Learning in Videos: The change detection methods can provide the free labels to develop self-supervised systems for several applications including object detection [201], video order prediction [202], and Video Representation Learning [203]. The future works include creating self-supervised algorithms by leveraging the existing CD methods. Such algorithms could also be extended to autonomous driving, intelligent surveillance, and anomaly detection.

VI. CONCLUSION

This paper presents an empirical review of the deep learning frameworks for change detection. Particularly, the existing CD methods are analyzed in terms of model design and evaluation frameworks. The variety of existing deep learning architectures are examined for their effectiveness to change detection. The CD methods are divided into broad categories and respective subcategories to provides a comprehensive review. The deep CD networks are analyzed based on the architecture design, network input, pretrained modules, finetuning, and auxiliary blocks. We notice that the supervised methods obtain superior
performance than the unsupervised methods. Several methods combine multiple heavy CNN modules to obtain higher performance which is matched by much smaller networks. It is observed that the pretrained models have limited effect on the performance and carefully designed lightweight networks also obtain good results on the benchmark datasets. Thus, the research challenge is to design the CNN network with minimal set of operations for motion analysis. Another key open challenge is to design resource efficient deep networks that can run at high speed over the CPU devices for real-time deployment.

The important categorization of the evaluation frameworks is presented as SIE, SDE, and CDE setups. Although, most of the existing works use the SDE to present their results, the SIE and CDE setups enforce a more stringent setting to test the generalization capability of the models. Thus, we encourage the researchers to report the SIE results for a robust evaluation of their deep CD methods. Similarly, other important challenges in robust CD, the current research needs, and future directions are discussed. We also described the related video datasets and the evaluation metrics of pixel-wise mask techniques. We believe this review will benefit the researchers in this field and provide useful insights into this important research topic. We hope to encourage more future work to develop in this direction.

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