Urban Change Detection Based on Remote Sensing Data

How are Recurrent Neural Networks applied in the context of urban change detection?

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Abstract

Urban change detection involves identifying and analyzing alterations in urban landscapes over time. This process is crucial for urban planning, environmental monitoring, and disaster management, as it provides insights into urban growth, land use changes, and human impact on the environment. This study focuses on Recurrent Neural Networks (RNNs) due to their ability to capture temporal dependencies, making them suitable for analyzing changes over time. In this research, an RNN model, specifically the SiamCRNN, was trained and evaluated on multiple datasets representing different urban scenarios. The model performed well in detecting urban changes, especially in datasets with higher spatial resolutions, but faced challenges with datasets characterized by high spectral range and complex urban structures. These findings underscore the importance of spatial resolution in influencing RNN model effectiveness for urban change detection tasks.

1 Introduction

The rapid pace of urbanization has significantly transformed landscapes worldwide, leading to extensive changes in land use, infrastructure, and socio-economic dynamics. As cities expand and evolve, monitoring these changes becomes increasingly crucial. Effective urban management requires up-to-date information to guide sustainable development, address environmental challenges, and ensure the well-being of urban populations. The growing complexity of urban areas necessitate robust methods to track and analyze these transformations accurately.

One of the most effective ways to monitor these dynamic changes is through urban change detection. Urban change detection entails the identification and analysis of transformations within urban areas over time. It involves comparing remote sensing data [11], such as satellite images or aerial photographs, captured at different times to identify changes in land use, infrastructure, vegetation, and other urban features.

The significance of urban change detection spans various domains. In urban planning, it helps in monitoring urban growth, guiding development, and ensuring sustainable land use. Environmental management benefits from understanding how urban expansion impacts natural resources and ecosystems. In disaster response, timely detection of changes can aid in assessing damage from natural disasters and planning recovery efforts. Socioeconomic studies use urban change data to analyze urban population trends.

Leveraging remote sensing data [11] is imperative for effectively monitoring these changes, as it provides comprehensive, high-resolution, and up-to-date information over large areas, enabling continuous and objective monitoring. This data can be obtained from various sources, including satellites, Unmanned Aerial Vehicles (UAVs), and aerial photography. The quality of remote sensing data [11] depends on the method of surface area scanning, which includes different sensors and technologies capable of capturing detailed spatial and temporal information. This capability is crucial for managing the dynamic and complex nature of urban environments.

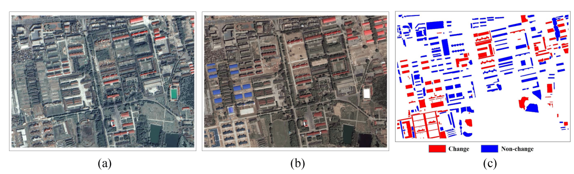

Figure 1: (a) Image acquired on 15 September 2004; (b) image acquired on 2 May 2005; (c) standard reference change map [14].

In Figure 1, we have an example of how urban changes are detected. The figure includes two images, one pre-change (a) and one post-change (b). The third image (c) shows where changes in the urban area are detected. In the change map, red indicates areas where changes have occurred, blue denotes areas with no change, and white areas are those not tracked for changes, typically non-building areas.

Despite the availability of various methods for urban change detection, there remains a gap in knowledge regarding the efficiency of Recurrent Neural Networks (RNNs) [15]. Traditional methods such as image differencing, principal component analysis (PCA) [8], and support vector machines (SVMs) [16] have been widely used, but they often struggle to capture temporal dependencies effectively. RNNs, on the other hand, have garnered attention due to their inherent capability to retain sequential information, making them well-suited for comprehending the temporal evolution of urban landscapes.

This paper aims to evaluate the effectiveness of RNNs for urban change detection by systematically training and assessing an RNN model on multiple unique datasets. Thus, it focuses on two model characteristics, namely the adaptability and performance in urban change detection tasks.

To thoroughly investigate the topic, the following research questions are defined:

- How do RNN operate, and why are they suitable for urban change detection?
- In what manner are RNNs specifically employed for detecting urban changes?
- What is the performance of RNNs in urban change detection across different scenarios?

By addressing these questions, this research aims to provide valuable insights into the applicability of RNNs for urban change detection. Such an evaluation is intended to contribute to decision-making processes in urban planning and management.

The structure of the paper is outlined as follows. First, background information on RNNs and their application in Urban Change Detection is provided. Next, in Section 3, we present and justify the chosen methodology. Section 4 details the experimental setup, while Section 5 presents the results of the experiment. Section 6 addresses responsible research, focusing on the ethical aspects and reproducibility of the study. In Section 7, we discuss and interpret the results. Finally, Section 8 offers the conclusions of the research and recommendations for future studies.

2 Background

This section provides the foundation necessary to understand the rest of the research. First the concept of RNNs is introduced, explaining their structure, functionality, and advantages, particularly in handling sequential data. This is followed by a detailed discussion on the application of RNNs in Urban Change Detection, describing the process from data collection to the interpretation of results. The aim of this section is to equip the reader with the needed knowledge to understand the methodologies and findings presented in the following sections.

2.1 Why Recurrent Neural Networks?

RNNs represent a specialized form of artificial neural networks tailored for processing sequential data. Unlike PCA [8] and SVMs [16], which treat each data point independently, RNNs maintain internal states across time steps, allowing them to capture temporal dependencies effectively.This inherent memory feature renders RNNs particularly adept at tasks reliant on understanding across temporal sequences, such as time series analysis and temporal pattern recognition.

At the core of an RNN lies the recurrent structure, which consists of an input layer, a hidden layer, and an output layer. What distinguishes RNNs from other neural network architectures is the incorporation of a feedback loop within the hidden layer. This loop enables the network to retain information across successive time steps. Mathematically, the hidden state at time step t (h_t) is computed as:

$$a_t = f(U \cdot x_t + W \cdot a_{t-1} + b) \tag{1}$$

where x_t represents the input at time t, U is the weight matrix governing the connections from the input to the hidden layer, W is the weight matrix governing the recurrent connections within the hidden layer, b is the bias vector for the hidden layer, and f denotes the activation function [10]. This formulation allows the RNN to effectively capture temporal dependencies and process sequential data efficiently by preserving information from previous inputs in its current hidden state.

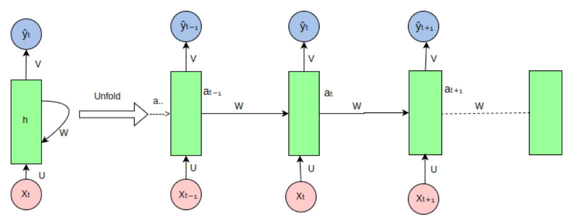

Figure 2: Architecture of a Recurrent Neural Network (RNN) [10].

RNNs present several advantages over traditional methods and alternative neural network architectures like Convolutional Neural Networks (CNNs).

Most notably, their inherent capacity to preserve temporal dependencies equips them with enhanced capabilities to capture the evolution of sequences over time. In contrast, while CNNs excel at spatial feature extraction, they lack the intrinsic mechanism to effectively incorporate temporal dynamics unless integrated with RNNs in a hybrid model.

2.2 Utilizing Recurrent Neural Networks for Urban Change Detection

This section provides a detailed exploration of the application of RNNs in Urban Change Detection. The process begins with the curation of temporal sequence data, typically comprising satellite images or aerial photographs captured at different time intervals. These sequential data provide a chronological view of the urban landscape's evolution.

Next, spatial features are extracted from each image in the sequence using Deep Learning Neural Networks like CNNs. These networks identify details such as buildings and roads.

Following feature extraction, RNNs are employed to capture temporal dynamics by retaining memory of previous inputs. This capability allows them to effectively comprehend sequence progression. By processing the sequence of feature maps derived from satellite images over time, RNNs can discern trends, patterns, and anomalies indicative of urban landscape transformations.

For example, in monitoring urban development over several years, a Siamese CNN compares pairs of images to detect isolated changes between specific time points. In contrast, a CNN-based RNN analyzes the entire sequence. It identifies gradual changes such as urban expansion or sudden shifts like new infrastructure projects. Leveraging its recurrent structure, the CNN-based RNN captures the temporal context of these changes, providing a deeper insight into urban development dynamics.

Upon processing sequence data, the extracted temporal features are fed into a classifier, often a fully connected neural network. It analyzes patterns, trends, and anomalies present in the temporal data to detect significant changes in the urban landscape. The classifier outputs predictions that pinpoint the locations and types of urban transformations observed, such as identifying new constructions, road expansions, or changes in green spaces.

The final stage involves interpreting and visualizing detected changes. Outputs from the classifier are typically post-processed to generate maps or reports highlighting significant urban transformations.

3 Methodology

In this section, the methodology employed in the research is presented, focusing on the selection, training, and evaluation of the RNN model for Urban Change Detection. We begin by explaining the process of selecting the appropriate RNN model, highlighting the advantages of various models considered, and justifying the choice of the Siamese Convolutional Recurrent Neural Network (SiamCRNN). Following this, we discuss the dataset collection, describing the different datasets chosen for training and evaluating the model, and their relevance to urban change detection. Finally, we outline the training and evaluation procedures, detailing the data handling, model configuration, and performance metrics used to assess the model's effectiveness.

3.1 Recurrent Neural Network Model Selection

The experiment begins with extensive research to select an appropriate RNN model for Urban Change Detection. Several models were considered, including Long Short-Term Memory (LSTM) networks [9], Gated Recurrent Units (GRUs) [5], Attention-based RNNs [13], and Siamese Convolutional Recurrent Neural Network (SiamCRNN) [4]. Each of these models has its strengths:

- **LSTM Networks**: Known for their ability to handle long-term dependencies and prevent the vanishing gradient problem [9].
- **GRUs**: Simplified versions of LSTMs that are computationally more efficient while still effectively capturing temporal dependencies [5].
- **Attention-based RNNs**: These models can focus on specific parts of the input sequence, making them highly effective for tasks where certain temporal features are more important than others [13].
- **Siamese Convolutional Recurrent Neural Network (SiamCRNN)**: Combines convolutional layers with recurrent connections, efficiently capturing both spatial and temporal features from sequential data [4].

Among these models, the SiamCRNN was selected for its specific advantages in urban change detection tasks. The model's Siamese architecture ensures that both inputs are processed identically, facilitating precise comparison and detection of changes between sequential urban data, such as satellite images captured at different times. By integrating convolutional layers, SiamCRNN extracts detailed spatial features, while its recurrent connections preserve contextual information over time, which is essential for comprehending temporal changes in urban environments. This holistic approach makes SiamCRNN particularly effective in scenarios requiring the detection of subtle and complex changes over time, such as urban planning, disaster response, and environmental monitoring.

Compared to LSTM networks, which excel in capturing long-term dependencies but may struggle with spatial feature extraction, and GRUs, which offer computational efficiency but with potentially reduced capability in handling complex spatial and temporal interactions, SiamCRNN strikes a balance by leveraging both convolutional and recurrent architectures. Additionally, Attention-based RNNs, while adept at focusing on critical temporal features, may lack the integrated spatial understanding provided by SiamCRNN's convolutional layers.

Moreover, the availability of SiamCRNN's architecture in an open repository [4] enhances its accessibility and reproducibility in research and practical applications. Figure 3 illustrates the architecture of SiamCRNN, emphasizing its integrated CNN and RNN layers within a Siamese framework.

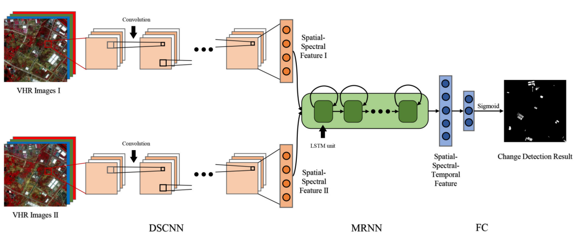

Figure 3: Architecture of a SiamCRNN [4].

3.2 Dataset Collection

Selecting appropriate datasets is crucial for training and evaluating the SiamCRNN model and make conclusions about the effectiveness of RNNs in Urban Change Detection. Several datasets were considered for this purpose, each with unique properties that make them suitable for different aspects of urban change detection: LEVIR-CD [3], CDD (Change Detection Dataset) [1], DSIFN-CD (Dual-Scale Image Fusion Network for Change Detection) [17], S2Looking [12], OSCD (Onera Satellite Change Detection) [2], WHU-CD [6], SYSU-CD [7].

For the experiment, four datasets were chosen to ensure a comprehensive evaluation of the SiamCRNN model:

- **LEVIR-CD:** This dataset features high-resolution images (1024 x 1024 pixels) with a medium spectral extent. The detailed annotations and high spectral resolution (typically 0.5 meters per pixel) make it ideal for training the model to accurately detect significant urban changes [3].
- **CDD (season-varying):** The CDD dataset includes images with dimensions of 256 x 256 pixelswith a low spectral extent. It focuses on seasonal variations, which allows for evaluating the model's adaptability to changes influenced by different seasons. The high spatial resolution of these images is essential for detecting detailed seasonal changes [1].
- **DSIFN-CD:** The DSIFN-CD dataset provides images with pixel dimensions of 256 x 256 and a medium spectral extend. This dataset includes multi-scale image pairs, helping to refine the model's ability to detect changes at various levels of detail across diverse urban scenarios. The moderate to high spatial resolution ensures that the model can analyze both fine details and broader contexts [17].
- **OSCD - 3ch:** The OSCD dataset stands out for its extensive coverage, often encompassing large urban areas such as entire cities, with images typically having larger pixel dimensions (e.g., 408 x 390). This dataset serves to challenge the model's robustness and efficiency in detecting urban changes across vast geographical extents. It also simulates real-world scenarios where spectral data may be limited, thus testing the model's adaptability under practical constraints [2].

By carefully selecting and utilizing these datasets, the experiment aims to thoroughly evaluate the SiamCRNN model's capability in urban change detection. This approach ensures a robust analysis of the effectiveness of RNNs in this domain, leveraging both high-resolution datasets and broader coverage datasets to capture a wide range of urban change scenarios.

3.3 SiamCRNN Model Training and Evaluation

The training and evaluation process of the SiamCRNN model begins with data handling, involving the extraction and preparation of training data through a custom dataset class that loads three-band (RGB) satellite images. This class processes image pairs (pre-event and post-event) and their corresponding change maps (labels). Data augmentation techniques, such as random cropping, flipping, and rotation, are applied during training to enhance the model's robustness. The images are normalized and formatted for the neural network.

The SiamCRNN model is tailored to the specific characteristics of the input data, emphasizing a fully convolutional architecture designed for large-scale change detection tasks. The model utilizes a ResNet as its encoder for robust feature extraction and integrates ConvLSTM layers along with Feature Pyramid Networks (FPN) in its decoder. This architecture ensures comprehensive utilization of both spatial and temporal information essential for accurate change detection [4].

During the training phase, the model generates change detection maps from paired input images. A dedicated training framework oversees model optimization and performance evaluation. Optimization employs a hybrid loss function combining cross-entropy and Lovasz-Softmax losses, specifically crafted to handle imbalances inherent in datasets. Parameter updates are managed using the AdamW optimizer, facilitating efficient convergence over a defined number of training epochs.

During training, the performance of the SiamCRNN model is regularly evaluated on a validation dataset using several key metrics to assess its efficiency in detecting urban changes. These metrics provide insights into different aspects of the model's performance:

- **Recall Rate:** Measures the proportion of actual positive cases (changes) correctly identified by the model. It is computed as:

$$\text{Recall} = \frac{TP}{TP + FN}$$

  where TP is the number of true positive predictions and FN is the number of false negatives.

- **Precision Rate:** Indicates the proportion of positive identifications made by the model that were correct. It is calculated as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

  where FP is the number of false positive predictions.

- **Overall Accuracy (OA):** Represents the proportion of correctly classified instances among the total number of instances. It is given by:

$$\text{OA} = \frac{TP + TN}{TP + TN + FP + FN}$$

  where TN is the number of true negative predictions.

- **F1 Score:** Harmonic mean of precision and recall, providing a balanced measure between the two metrics:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

- **Intersection over Union (IoU):** Measures the overlap between predicted and ground truth change regions. It is computed as:

$$IoU = \frac{\text{Area of Intersection}}{\text{Area of Union}}$$

  This metric is particularly useful for evaluating spatial overlap accuracy.

- **Kappa Coefficient:** Evaluates the agreement between predicted and actual changes, considering the possibility of random agreement:

$$\kappa = \frac{p_o - p_e}{1 - p_e}$$

  where p_o is the observed agreement and p_e is the expected agreement by chance.

These metrics collectively provide a comprehensive evaluation framework for assessing the SiamCRNN model's performance in urban change detection tasks.

4 Experiment Setup

The experiments were conducted using Jupyter Notebooks hosted on Google Colab, leveraging T4 GPUs to maximize computational efficiency during both training and evaluation phases. To replicate the experiment on Google Colab for the Levir-CD dataset as an example, the following steps were undertaken:

1. **Clone Repository:** Clone the SiamCRNN repository from GitHub using the following link:
   https://github.com/ivan0103/SiamCRNN.
2. **Download Levir-CD Dataset**
3. **File Structure Adjustment:** Execute the `files.sh` script located within the project repository at "FCN_version/script". This script adjusts the file hierarchy of the dataset to match the preferred format of the SiamCRNN model.

   Figure 4 illustrates the structure of the modified dataset folder used for training and evaluating the model.

```
folder/
├── pair/
│   ├── img1.jpg
│   └── img2.jpg
└── cm/
    └── cm.png
```

   Figure 4: Structure of the modified dataset folder.

   Within each subfolder, the "pair" folder contains pairs of images depicting the pre-change and post-change states for every sample in the dataset. Correspondingly, the "cm" folder in the same subfolder stores the respective change map image. This consistent structure is replicated across all subfolders, ensuring that the entire dataset is uniformly organized.

   Algorithm 1, located in Appendix A.1, shows the pseudocode outlining the file hierarchy modification process using the `files.sh` script.
4. **Add Dataset to Google Colab:** Upload the modified dataset to your Google Drive folder (`MyDrive/Colab Notebooks`) for access within the Google Colab environment.
5. **Execution:** Open a Google Colab notebook, clone the repository inside the notebook environment, navigate to the appropriate directory, and execute the main Python script (`train_siamcrnn.py`) to commence model training and evaluation. Algorithm 2, located in Appendix A.2, shows an example of setting up and executing the experiment in Google Colab using a Python script.

5 Results

This section presents the outcomes of the SiamCRNN model's performance on four chosen datasets. Each dataset is evaluated based on key metrics, that provide a comprehensive assessment of the model's ability to detect urban changes accurately. The results highlight the strengths and areas for improvement in the model's performance across different datasets, offering insights into its robustness and effectiveness in urban change detection.

5.1 OSCD Dataset

Evaluation Criteria	Accuracy
Recall Rate	0.5619
Precision Rate	0.4217
Overall Accuracy (OA)	0.9375
F1 Score	0.4819
Intersection over Union (IoU)	0.3174
Kappa Coefficient	0.4493

Table 1: Evaluation Metrics on OSCD Dataset

The model shows strong OA and moderate agreement in detecting urban changes. However, there is a notable imbalance between recall and precision rates, indicating a need for improving the model's ability to reduce false positives while maintaining or improving sensitivity to true positives. The F1 score and IoU also reflect areas where further refinement could enhance the model's performance in accurately identifying and delineating urban changes. Overall, while the model performs well in overall accuracy and agreement metrics, addressing precision-recall balance and spatial accuracy could lead to more robust urban change detection results on the OSCD dataset.

5.2 Levir-CD Dataset

Evaluation Criteria	Accuracy
Recall Rate	0.8904
Precision Rate	0.8104
Overall Accuracy (OA)	0.9838
F1 Score	0.8485
Intersection over Union (IoU)	0.7369
Kappa Coefficient	0.8400

Table 2: Evaluation Metrics on Levir-CD Dataset

The model shows very high recall and precision rates, indicating strong sensitivity and specificity in detecting urban changes. The OA and F1 score further highlight the model's robust performance, with a good balance between true positive identification and minimizing false positives. The high IoU and Kappa coefficient scores demonstrate substantial spatial accuracy and strong agreement in change detection, respectively. Overall, the SiamCRNN model performs exceptionally well on the Levir-CD dataset, effectively capturing and delineating urban changes with high accuracy and reliability.

5.3 CDD Dataset

Evaluation Criteria	Accuracy
Recall Rate	0.8866
Precision Rate	0.7318
Overall Accuracy (OA)	0.9483
F1 Score	0.8018
Intersection over Union (IoU)	0.6692
Kappa Coefficient	0.7724

Table 3: Evaluation Metrics on CDD Dataset

The high recall rate indicates that the model is very effective at identifying true positives, while the relatively high precision rate shows a good ability to avoid false positives. The OA and F1 score underscore the model's ability to correctly identify changes and minimize false identifications. The high IoU score reflects substantial spatial accuracy in delineating changes, and the strong Kappa coefficient indicates robust agreement in change detection. Overall, the SiamCRNN model performs very well on the CDD dataset, effectively capturing and delineating urban changes with high accuracy and reliability.

5.4 DSIFN-CD Dataset

Evaluation Criteria	Accuracy
Recall Rate	0.9827
Precision Rate	0.6218
Overall Accuracy (OA)	0.8004
F1 Score	0.7617
Intersection over Union (IoU)	0.6151
Kappa Coefficient	0.6044

Table 4: Evaluation Metrics on DSIFN-CD Dataset

The model achieves an exceptionally high recall rate, indicating a very strong ability to detect nearly all true positives. However, the precision rate suggests a relatively high rate of false positives, indicating room for improvement in specificity. The OA shows moderate performance in general classification tasks, while the F1 score reflects a reasonable balance between recall and precision. The IoU indicates moderate spatial accuracy in delineating changes. The Kappa coefficient of 0.6044 suggests moderate agreement between predicted and actual changes, considering chance agreement. Overall, while the model is highly sensitive in detecting changes, efforts to improve precision and spatial accuracy could enhance its overall effectiveness on the DSIFN-CD dataset.

6 Responsible Research

The section provides a concise overview of the key concerns regarding reproducibility and ethical considerations in the research.

To uphold transparency and credibility, all experiment details are publicly available, both within the paper and on the project's GitHub repository. Replication studies are strongly recommended using varied datasets, given the specialized nature of satellite imagery, along with diverse training configurations to validate and ensure the accuracy of the chosen methodologies.

High-resolution satellite imagery has the capability to capture sensitive data pertaining to individuals and private properties. To mitigate privacy risks, data anonymization is imperative, adhering to regulations such as GDPR to guarantee the exclusion of identifiable information.

7 Discussion

In this section, we analyze the results from the experimental evaluation of the SiamCRNN model and discuss the efficacy of RNNs in urban change detection.

The SiamCRNN model demonstrates strong performance in urban change detection, achieving high recall rates, overall accuracy, and F1 scores across multiple datasets, particularly on Levir-CD and CDD. These metrics highlight its effectiveness in detecting changes in urban structures, which is crucial for tasks like urban monitoring.

The high performance of the SiamCRNN model on the Levir-CD, CDD, and DSIFN datasets suggests that the model is highly effective in detecting urban changes in environments with well-defined and high-resolution spatial characteristics. These datasets are characterized by clear and distinct changes in urban structures, which likely contribute to the model's ability to accurately detect and delineate changes. For example, the Levir-CD dataset includes high-resolution imagery of urban areas with distinct building changes, allowing the model to leverage its spatial-temporal capabilities effectively. Similarly, the CDD dataset features high-quality images with pronounced urban changes, facilitating precise detection by the model. The strong metrics on the CDD dataset also indicate the model's robustness in detecting urban changes even through seasonal variations, highlighting its adaptability to different temporal conditions. The DSIFN-CD dataset, despite some variability in its performance metrics, still showcases high recall rates, indicating the model's sensitivity to actual changes. This highlights the model's robustness in detecting urban changes across diverse environments, encompassing both rural and urban settings. Overall, these strong results suggest that the SiamCRNN model is particularly well-suited for applications in urban environments where changes are clearly visible and the data quality is high. This underscores the importance of high-resolution imagery and well-defined urban change features in achieving optimal model performance. Additionally, the consistency in performance across these datasets highlights the model's robustness and adaptability to different urban settings.

However, the model's performance on the OSCD dataset is notably lower. This outcome can be attributed to a combination of factors specific to OSCD. Firstly, the dataset's lower spatial resolution introduces challenges in capturing changes accurately. This limitation is compounded by the dataset's high spectral range and the expansive coverage of very urban environments, including major cities like Rio de Janeiro, Paris, Dubai, and Hong Kong. These factors introduce significant variability in urban structures, lighting conditions, and environmental contexts. Moreover, the OSCD dataset's smaller training and test sets further constrain the model's ability to generalize effectively across diverse urban scenes. Consequently, the dataset has a very low spatial resolution, which significantly impacts the model's performance in detecting subtle and complex urban changes. The lower performance on the OSCD dataset is primarily due to its lower spatial resolution, high spectral range, insufficient image resolution, and complex urban environments, rather than an inherent weakness of the model. Lower spatial resolution reduces the level of detail in the imagery, making it more challenging for the model to detect subtle urban changes effectively.

In conclusion, while the SiamCRNN model excels on datasets with higher spatial resolutions such as Levir-CD and CDD, its performance diminishes on datasets like OSCD with lower spatial resolutions.

8 Conclusion

Urban change detection is pivotal for monitoring and managing transformations within urban environments over time, crucial for urban planning, environmental sustainability, and disaster management. This study evaluated the effectiveness of RNNs, utilizing remote sensing data [11] to detect and analyze urban changes.

Traditional methods like PCA and SVMs have limitations in capturing temporal dependencies essential for understanding the evolution of urban landscapes. In contrast, RNNs excel in this regard due to their capability to retain and utilize sequential information, offering significant advantages in comprehending the temporal dynamics of urban growth, infrastructure development, and environmental changes. The SiamCRNN model, a specialized RNN implementation tailored for change detection, was specifically chosen for this study to assess the efficacy of RNNs in urban change detection.

The findings highlight the robust performance of the SiamCRNN model across various datasets. It achieved high recall rates, precision, overall accuracy, and F1 scores, demonstrating its effectiveness in identifying significant changes in urban features, particularly buildings. However, the study also revealed challenges, particularly evident on datasets with lower spatial resolutions and complex urban structures. The SiamCRNN model exhibited diminished performance on the OSCD dataset, primarily due to its lower spatial resolution and the inherent complexity of urban environments covered. This emphasizes the critical role of spatial resolution in influencing the model's effectiveness for urban change detection tasks.

Future research directions should focus on enhancing the adaptability of the SiamCRNN model to diverse urban scenarios and varying data qualities. Continuous innovation is essential to address current limitations and explore new avenues for improving the effectiveness of RNNs in urban change detection. Specifically, evaluating the SiamCRNN on datasets with lower spatial resolutions will provide further insights into its robustness across different urban environments. Additionally, exploring alternative RNN methods such as LSTM, GRU, and Attention-based RNNs for Urban Change Detection will offer a comprehensive understanding of their capabilities and comparative effectiveness. This comparative analysis will guide the refinement and development of RNN frameworks tailored to effectively address urban change detection challenges.

In conclusion, while the SiamCRNN model demonstrates strong performance on datasets with higher spatial resolutions, its effectiveness diminishes on datasets with lower spatial resolutions like OSCD. This underscores the importance of spatial resolution in urban change detection and emphasizes the need for ongoing research to enhance model adaptation and improve performance across diverse urban environments.

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A Algorithms

A.1 Algorithm used for modifing dataset file hierarchy.

Algorithm 1 Pseudocode for Modifying File Hierarchy

$source\_dir\_A \leftarrow$ path to 1st training image
$source\_dir\_B \leftarrow$ path to 2nd training image
$source\_dir\_Label \leftarrow$ path to training label
$destination\_dir \leftarrow$ destination to move files
$train\_dir \leftarrow destination\_dir + "/training"$
$output\_file \leftarrow destination\_dir + "/train.txt"$
$test\_dir \leftarrow destination\_dir + "/testing"$
$output\_file \leftarrow destination\_dir + "/test.txt"$
for each $file$ in $source\_dir\_A/*.jpg$ **do**
    $filename \leftarrow$ get_base_filename($file$)
    create_directories($train\_dir, filename$)
    create_directories($train\_dir\_filename, pair$)
    create_directories($train\_dir\_filename, cm$)
    copy_files_to_pair_folder($source\_dir\_A$)
    copy_files_to_pair_folder($source\_dir\_A$)
    copy_to_cm_folder($source\_dir\_Label$)
    filename_to_output_file($filename, output\_file$)
end for

A.2 Pseudocode for training the SiamCRNN model in a Google Colab environemtn with Levir-CD dataset

Algorithm 2 Example Execution of NumPy File in Google Colab

```
!git clone
https://github.com/ivan0103/SiamCRNN.git
from google.colab import drive
drive.mount('/content/drive')
%cd SiamCRNN
!git checkout Levir-CD
%cd FCN_version
!pip install -r requirements.txt
%cd script
!python train_siamcrnn.py
```

B Usage of ChatGPT

This appendix provides context on the usage of ChatGPT for the project.

B.1 Improving Text

ChatGPT was employed to enhance the clarity, professionalism, and overall quality of the written content. The following tasks were performed:

- **Refinement of Draft Text:** ChatGPT assisted in refining draft text for different findings and analysis, conclusions, results, and methodologies. This helped in making the content more concise, clear, and professional.

B.2 Code Assistance

ChatGPT provided valuable assistance in managing and updating the project's code repository. Specific tasks included:

- **Updating Repository Imports:** Helped with updating and correcting imports within the repository to ensure compatibility and functionality of the scripts.
- **Script for File Formatting:** Assisted in writing a script for file formatting, mentioned in Appendix A.1.

B.3 Formatting LaTeX

ChatGPT was instrumental in helping to format various elements in LaTeX, which included:

- **Writing Tables:** Assisted in the creation and formatting of tables in LaTeX, ensuring they were correctly structured and visually appealing.
- **Formulating Formulas:** Provided help with writing complex formulas in LaTeX, ensuring mathematical expressions were accurately represented.
- **Writing Algorithms and Pseudo codes:** Helped in writing and formatting algorithms in LaTeX, making sure they were clearly presented and easy to follow.