Research on Remote Sensing Image Target Recognition and Image Change Detection Algorithm Based on Deep Learning

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***Abstract*—Deep learning is a deep field of neural networks, and its application in remote sensing image classification and recognition processing has attracted attention and discussion from all walks of life. This paper first briefly introduces the traditional remote sensing image processing methods and the limitations of these algorithms and emphasizes the limitations of these techniques. Then, the research status of target recognition and change detection in remote sensing images based on deep learning is discussed, and how to select and design appropriate deep learning models. And then, the datasets of two different provinces were selected for comparative experiments, and the implementation process of target recognition and change detection in remote sensing images was described in detail. Finally, based on the experimental results, the future trend of deep learning application in remote sensing identification and classification is prospected.**

***Keywords*—remote sensing image processing, deep learning, target recognition, change detection, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN)**

I. INTRODUCTION

In this study, we explore the application of deep learning algorithms in remote sensing image target recognition and change detection. We aim to address the limitations of traditional methods by leveraging the powerful feature learning capabilities of deep learning models. Specifically, we focus on the selection and design of appropriate deep learning architectures, data preprocessing and enhancement techniques, training and optimization strategies, as well as the evaluation and visualization of results. Through rigorous experiments and comparisons, we aim to demonstrate the effectiveness of deep learning in enhancing the accuracy and reliability of remote sensing image processing tasks. The findings of this study have the potential to significantly advance the field of remote sensing and geospatial intelligence, enabling more accurate and efficient monitoring, analysis, and decision-making in various practical applications.

II. RELATED WORK

A. Traditional Remote Sensing Image Target Recognition and Change Detection Methods

In terms of target recognition, traditional methods typically involve thresholding, filtering, and feature extraction steps. Thresholding is used to segment objects from the background based on pixel intensity values. Filtering techniques, such as Gaussian blurring or median filtering, are employed to reduce noise and enhance specific features. Feature extraction, on the other hand, aims to identify discriminative characteristics of interest, such as texture, shape, or color, using hand-designed algorithms. These extracted features are then used in classifiers like Support Vector Machines (SVM) or Random Forests to distinguish between different target categories.

For change detection, traditional methods often compare sequential remote sensing images to identify temporal variations [1]. Pixel-based approaches, such as difference imaging, calculate the difference between corresponding pixels in different time periods. Change vectors, on the other hand, consider multiple spectral bands to detect changes in vegetation, water bodies, or urban areas. Thresholds are typically applied to these difference images to identify significant changes [2].

However, traditional methods often face challenges when dealing with complex and dynamic remote sensing scenes. Hand-crafted features may not generalize well across different datasets and scenarios, leading to limited accuracy and robustness. Additionally, these methods often require extensive preprocessing and parameter tuning, which can be time-consuming and computationally expensive.

Moreover, traditional remote sensing image processing techniques often treat each image independently, ignoring the temporal and spatial relationships between pixels and objects [3]. This can lead to inaccuracies in target recognition and change detection, especially in scenarios with significant temporal variations or complex spatial patterns.

In conclusion, while traditional remote sensing image target recognition and change detection methods have provided valuable insights in the past, they often struggle with the increasing complexity and diversity of modern remote sensing data. To address these limitations, there is a need for more advanced and adaptive approaches that can effectively handle the unique challenges posed by remote sensing imagery.

B. Limitations and Challenges of Current Research

Although deep learning has achieved remarkable progress in remote sensing image processing, there are still several limitations and challenges that need to be addressed [3, 4]. This section explores these limitations and challenges in detail.

1) Limitations

- Collecting and annotating remote sensing images require expertise and significant resources, limiting the availability of large-scale labeled datasets.
- Training deep learning models, especially large-scale ones, requires significant computational resources. This can be a limitation for researchers and organizations with limited access to high-performance computing facilities.
- While deep learning models have achieved impressive

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performance on specific tasks, their generalization capabilities can still be limited. Models trained on one dataset may not perform well on another dataset with different characteristics, posing a challenge for their application in real-world scenarios.

- Deep learning models, especially complex ones like deep neural networks, lack interpretability. This makes it difficult to understand why a model makes a particular prediction, which can be crucial for decision-making in remote sensing applications.

2) Challenges

- Improving the accuracy of deep learning models often comes with a trade-off in efficiency. Developing models that can achieve both high accuracy and fast inference speeds remains a challenge in remote sensing image processing.
- Remote sensing images can vary significantly in terms of resolution, sensor type, and acquisition conditions. Developing robust models that can handle this heterogeneity and produce consistent results is a key challenge.
- In remote sensing image processing, certain classes may be significantly more prevalent than others, leading to class imbalance issues. This can affect the performance of deep learning models, making it challenging to accurately detect or classify minority classes.
- While deep learning has made significant progress, traditional remote sensing methods still have their merits. Developing frameworks that can effectively integrate deep learning with traditional methods to leverage their complementary strengths is a key challenge for future research.

In conclusion, current research in deep learning for remote sensing image processing faces several limitations and challenges. Addressing these issues and overcoming the associated hurdles will be crucial for the field and realizing the full potential of deep learning in remote sensing applications.

III. Methodology

A. Selection and Design of Deep Learning Model

1) Convolutional Neural Network (CNN)

CNN is a feed-forward neural network, its artificial neurons only respond to the local range of units, local feature extraction within a certain feeling field of view achieved by convolutional operations, at the same time, due to the number of neural units is much less, mitigating overfitting, and layer by layer to learn the deeper features of the input image, in addition to the CNN it has a certain degree of invariance to the observation of the image rotation, translation, scaling and other objectives, in large-scale image processing has a very good performance [5]. Usually the classical convolutional neural network consists of convolutional layer, pooling layer, and fully connected layer.

- Convolutional layer. The convolutional layer is composed of a number of convolution operators (convolution kernels), the convolution kernels (each layer of fixed size) slide over the image and do convolution operations to obtain a feature map. A variety of different image features are obtained through convolution operations, in the shallow layer of the neural network are low-level features such as edges, angles, etc., with the deepening of the network, in the deeper layer of the neural network can be extracted geometry, spatial relationships, and other high-level features, and each convolution kernel's parameters are regarded as the nodes in the neural network, which are optimized and obtained by the back-propagation algorithm. The size of the convolution window reflects the size of the sensory field of view, the larger the window the larger the field of view and the more parameters, and if it is a 1×1 convolution window is generally used for dimensionality reduction, Fig. 1 is an example of the feature map obtained by convolution window.

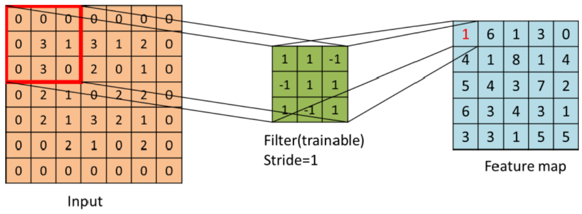


Fig. 1. Convolutional layer.

- Pooling layer, usually the feature map obtained after the convolutional layer will have a higher dimension, the feature map can be sliced by the pooling layer, and the maximum value (or average value) can be taken in different regions after the slicing to get a feature map with a smaller dimension. For example, Fig. 2 is an example of a pooled feature map, with the original feature map in the middle, and (a), (b), and (c) indicate that they are the results of maximum pooling, average pooling, and global average pooling, respectively.

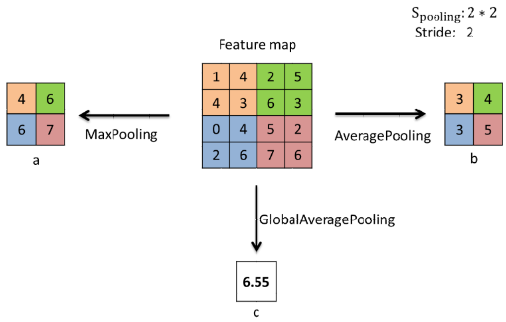


Fig. 2. Pooling layer.

- Fully connected layer. The role of the fully connected layer is to turn the local features obtained earlier into global features through the traditional fully connected neural network, the fully connected layer is a normal neuron to neuron fully connected, the output is calculated through the Softmax function to get the probability value of the different categories, the output probability value of the largest that is, the category of the picture Convolutional neural network in the number of convolutional layers, the size of the pooling layer pooling method, number of Different combinations of different types of convolutional neural network models can be obtained, such as the current common models are: LeNet, AlexNet, VGG, GoogleNet, ResNet, etc.

2) Recurrent Neural Network (RNN)

The biggest feature of RNN is that it receives data from different moments through a neural unit with cyclic inputs, so that the output of the next moment is affected by the input of the previous moment. This cyclic network structure is very suitable for dealing with time-series data (e.g., speech, sentences, etc.), and the network can memorize the before-and-after dependencies in the data. However, it was later found that early RNNs were prone to two problems due to iteration: one is that it is difficult to realize the long-term preservation of information, and the other is the existence of gradient disappearance and gradient explosion. Therefore, early RNNs were not widely used. Later, Hochreiter *et al.* improved the traditional RNN model by proposing Long Short-Term Memory Networks (LSTM), which is the most effective sequence model in practical applications today, LSTM is more complex than RNN in terms of its hidden unit structure. LSTM is more complex than RNN, through the improvement of hidden unit structure, LSTM can selectively memorize or forget the input information. As scholars continue to research, there are various variants of RNNs, such as gated recurrent units, which are simpler than LSTMs. Schuster *et al*. proposed a bidirectional recurrent neural network, in which the recurrent structure of Bi RNN can learn contextual dependencies in two temporal directions (the current state to the past state, and the past state to the current state) through two different hidden layers. Learning contextual dependencies.

B. Data Preprocessing and Enhancement Technology

Data preprocessing and enhancement technology play a pivotal role in ensuring the quality and effectiveness of data analysis. These techniques aim to transform raw data into a more structured, relevant, and useful format for subsequent analysis [6]. By applying preprocessing and enhancement methods, researchers and analysts can enhance the interpretability and reliability of their findings.

1) Data preprocessing

Data preprocessing is the initial stage of data analysis, which involves cleaning, transforming, and organizing raw data to make it suitable for analysis. This process involves several steps, such as handling missing values, dealing with outliers, normalizing data, and feature scaling. By addressing issues like incomplete or incorrect data, preprocessing ensures that the data is accurate, consistent, and ready for further analysis.

2) Data enhancement

Data enhancement techniques aim to improve the quality and quantity of data by generating new, relevant information from existing data. This can include techniques like oversampling, undersampling, or synthetic data generation to balance out classes in a dataset. Other enhancement methods may involve feature engineering, where new features are derived from existing ones to capture more information or improve the predictive power of models.

C. Training and Optimization Strategies

1) Training strategies

Training strategies refer to the approaches used to train machine learning models. They involve selecting the right algorithm, setting hyperparameters, and managing the training dataset. Training strategies aim to ensure that the model learns the underlying patterns and relationships in the data effectively [7]. This includes techniques such as batch training, where the model is trained on a subset of the data at a time, and online learning, where the model updates its parameters as new data becomes available.

2) Optimization strategies

Optimization strategies focus on improving the performance of machine learning models. They aim to minimize the error rate or maximize the accuracy of predictions made by the model. Optimization techniques can be classified into two broad categories: gradient-based optimization and heuristic optimization. Gradient-based optimization methods, such as gradient descent, use the gradient of the loss function to update the model parameters. On the other hand, heuristic optimization methods, such as genetic algorithms or simulated annealing, rely on trial-and-error to find the best set of parameters.

The choice of training and optimization strategies depends on the specific requirements of the problem and the nature of the data. For example, in scenarios where the dataset is large and computational resources are limited, online learning or mini-batch training may be preferred. Similarly, for complex models or datasets with noisy labels, advanced optimization techniques may be necessary to achieve good performance.

D. Implementation Process of Remote Sensing Image Target Recognition

- The first step involves acquiring high-quality remote sensing images. These images are typically captured by satellites or drones and may cover a wide area [8]. Preprocessing steps include geometric correction, radiometric calibration, and noise reduction to ensure that the images are suitable for further analysis.
- Segmentation is the process of dividing the image into distinct regions or objects. This can be achieved using techniques such as thresholding, edge detection, or region-based methods. Once the image is segmented, feature extraction techniques are applied to extract meaningful information from each segment. These features can include shape, size, texture, color, and contextual information.
- The next step involves detecting and classifying the targets of interest in the image. This can be achieved using various algorithms and techniques, such as Support Vector Machines (SVMs), random forests, Convolutional Neural Networks (CNNs), or deep learning models. These algorithms learn to recognize patterns and relationships in the extracted features and use them to identify and classify the targets.
- After target detection and classification, post-processing steps may be performed to improve the accuracy and reliability of the results. This can include techniques such as smoothing, filtering, or merging overlapping detections. Evaluation metrics, such as precision, recall, and F1-score, are used to assess the performance of the recognition system.
- Finally, the implemented target recognition system is

integrated into a larger system or platform for deployment. This may involve integrating the recognition system with a Geospatial Information System (GIS) or a remote sensing data processing pipeline. The deployed system is then used to monitor and analyze remote sensing imagery, providing valuable insights and information for various applications, such as environmental monitoring, urban planning, or disaster response.

E. Strategy and Technology of Image Change Detection

The first step is to define the specific changes of interest. This could involve monitoring land use changes, detecting new construction, or tracking the spread of a natural disaster [1].

Collecting a time series of images is essential [9]. These images should cover the same geographical area and have sufficient temporal resolution to capture the desired changes.

Images are preprocessed to ensure they are comparable. This may include radiometric normalization, geometric correction, and registration.

Algorithms are chosen based on the type of changes being monitored and the characteristics of the imagery. Algorithms range from simple pixel-based methods to complex object-oriented approaches.

Change detection results are validated using ground truth data, such as field surveys or existing maps, to assess accuracy. Implementing a system for regular monitoring ensures changes are tracked over time.

Utilization remote sensing platforms provide the imagery needed for change detection, Geospatial Information Systems (GIS) provide a spatial context for change detection, enabling analysis and visualization of changes within a geographical framework, Machine Learning and Deep Learning enhance change detection accuracy [10].

Utilization automated workflows and cloud computing dispose efficient batch processing of large volumes of imagery and rapid processing and analysis of large datasets.

F. Visualization and Evaluation Methods of Results

In the field of image change detection, visualization and evaluation of results are crucial steps that enable analysts to interpret the detected changes and assess their accuracy and reliability. Effective visualization techniques provide intuitive representations of the changes, while evaluation methods provide quantitative assessments of the performance of the change detection algorithms.

1) Visualization methods

- These images display the original scene before the change and the scene after the change, allowing analysts to visually compare the differences.
- These images represent the direct pixel-wise differences between the before and after images. They highlight the regions where changes have occurred.
- Change maps provide a spatially explicit representation of the detected changes. Each pixel or region is assigned a value indicating the type and magnitude of change.
- These composites use color-coding to visualize changes. Different colors represent different types or degrees of change, making it easier to identify and interpret changes.

2) Evaluation methods

- Accuracy assessment involves comparing the detected changes with reference data or ground truth. Metrics such as overall accuracy, precision, recall, and F1 score are commonly used to evaluate the performance of change detection algorithms.
- Kappa statistics, particularly Kappa coefficients, are used to assess the agreement between the change detection results and the reference data, considering the accuracy expected by chance.
- ROC analysis evaluates the performance of a change detection algorithm by plotting the true positive rate against the false positive rate for different threshold settings. The area under the ROC curve (AUC) provides a single metric for comparing the performance of different algorithms.
- Cross-validation techniques, such as k-fold cross-validation, are used to assess the generalization performance of change detection models by dividing the data into training and testing sets.
- In addition to quantitative metrics, qualitative evaluation is also important. Analysts visually inspect the change maps and other visualizations to assess their coherence, consistency, and interpretability.

IV. Experiments and Results

A. Description and Preprocessing of Data Sets

In this paper, two datasets are selected for comparison experiments, the data source of the first dataset is from Wuhu City, Anhui Province, China, with the size of 1669x1368 square meters area, and the two time-phase images have gone through the image fusion and image alignment pre-processing operations, the former time-phase is the 1-meter-resolution satellite true-color image of March 2013, as shown in Fig. 3(a), and the latter time-phase is the June 2013 0.5 m resolution UAV true color image, as shown in Fig. 3(b). The main features include buildings, bare soil, vegetation, and roads, and the main change is from bare soil to buildings. The real changes are obtained by combining a priori information and manual interpretation based on the input images in Fig. 3(a) and (b) as shown in Fig. 3(c).


(a) (b) (c)

Fig. 3. Dual time-phase remote sensing image of an area in Wuhu city, Anhui province, China.

The data source of the second dataset is from Jingzhou City, Hubei Province, China, the size of the area of 615×586 square meters both time-phase images have been image fusion, image alignment pre-processing operations, the front time-phase is the true color image of November 2015 (China Gaofen 2, resolution 1 m), as shown in Fig. 4(a), and the back time-phase is the true color image of November 2016 (France PLEIADES 1B, resolution 0.5 m), as shown in Fig. 4(b). The background of the experiment is the 2015-2016 Land Use

Change Survey (LUCS) in Hubei, China.The main types of land use in the region include buildings, farmland, vegetation and roads. November is the season of rice harvesting in the region, in the pre-temporal image most of the rice is ripe and harvested, which makes most of the farmland has bare soil characteristics, but most of the rice in the post-temporal image is ripe but not harvested, which makes most of the farmland has vegetation characteristics, for these farmland before and after the image of the land-use type did not change. As shown in Fig. 4(c), the real changes are obtained by combining a priori information and manual interpretation based on the input images in Fig. 4(a) and (b). There are three main types of land use changes in the region: changes from vegetation to buildings (change A, red area in Fig. 4(c)), changes from bare soil to buildings (change B, yellow area in Fig. 4(c)) and changes from farmland to roads (change C, blue area in Fig. 4(c)).

Fig. 4. Dual-time remote sensing image of an area in Jingzhou city, Hubei province, China.

B. Experimental Settings and Parameter Adjustment

In this paper, we propose two kinds of change detection models based on, firstly, preprocessing of two different simultaneous images, HasterR-after the time-phase quasi-uniform coordinate reference system and image resolution, one kind of the two different simultaneous images will be merged by waveforms first, and then sent to the Faster R-CNN for detection (MFRCNN), and one kind of the difference image is generated according to the two different simultaneous images, and then sent to the Faster R-CNN for detection (SFRCNN), the training samples of the two models are also processed accordingly, and the detection result is a series of rectangular regions, and then the rectangular regions with the same change type and intersections are fused, and then finally segmented to get the exact change region using the Snake model.

The basic principle of the Snake model is to assume that there is a set of curves to be selected that contains the result of our segmentation, define an energy function that describes a certain target attribute of the curves in the set of curves to be selected, such as the curve continuity, the maximum gradient and so on, and when the curve boundaries change within the range of the value, the energy function reaches a minimum value so that the curve maintains the convergence of the smooth convergence conditions converge to the target boundaries, that is, the result of the segmentation. The Snake model deforms the curve by controlling the parameters to minimize the energy objective function, the control parameters include the internal force and the external force, the internal force is to keep the curve as smooth as possible, the external force is to let the curve gradually match the local characteristics of the image, and the final segmentation process is transformed into the process of finding the minimum value of the energy function.

C. Comparative Experiment and Analysis

Three types of samples are manually selected, including vegetation to buildings, bare soil to buildings, and farmland to roads, in which about 200 samples are selected for each type of change, and the length and width of the samples are between 200-800 pixels, and the sample size can be inconsistent, the sample set consists of before and after time-phase images as well as the corresponding XML or JSON files (used to record the border coordinates of the change area). Examples of the collected samples are shown in Fig. 5.

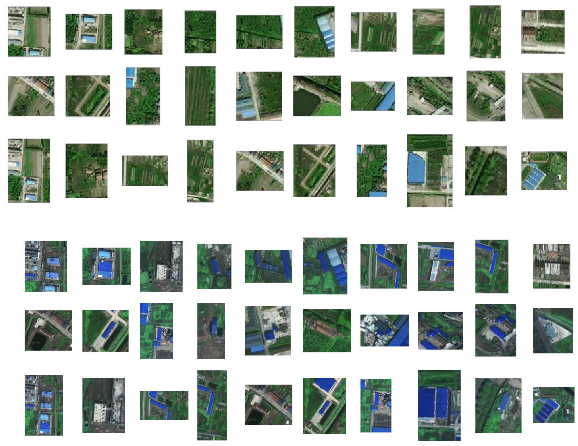


Fig. 5 (a). Time-phase sample before the vegetation change building; (b). Ti me-phase sample after the change from vegetation to building.

D. Results Presentation and Discussion

Use the public dataset to train part of the network (shared convolutional layers), and use your own dataset to fine-tune the network in other layers; secondly, through the data expansion technique, which is a method to improve the generalizability of the network without spending additional training time (A1en, 1974). When we trained the model, the original samples were shifted horizontally and vertically by 0-30% and flipped, and then randomly rotated by 0-45° angle and then shifted and flipped again to expand the number of samples to 7 times of the original, as shown in Fig. 6 and Fig. 7.

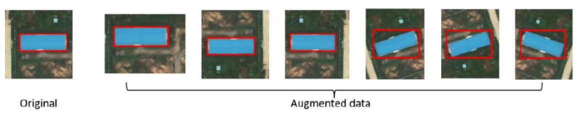


Fig. 6. Data expansion.

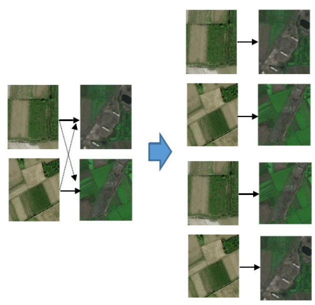
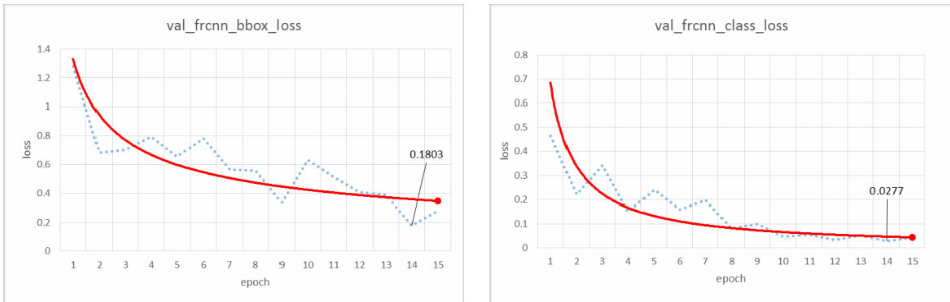


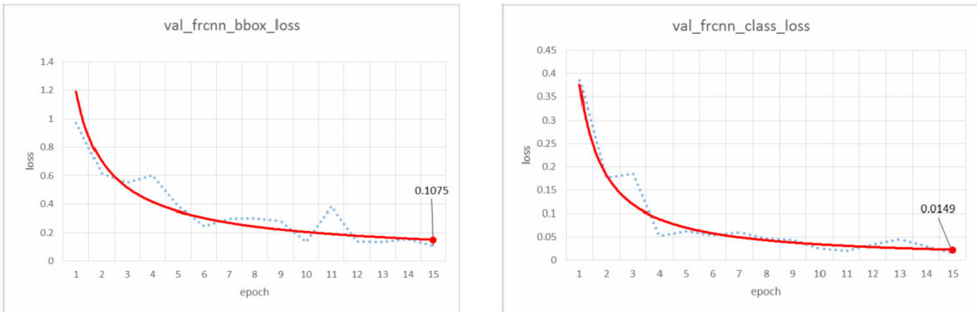
Fig. 7. Change detection sample pair manual expansion.

The main training parameters of the model are as follows: RPN prediction window size (64, 128, 256}; non-great value suppression (if there are two boxes overlap more, the low probability of elimination) value of 0.7; the use of SGD combined with momentum optimization method: learning rate of 0.001, momentum of 0.9, as shown in Fig. 8: the network regularization weight attenuation coefficient of 0.0001: the loss of multitasking weight coefficients are all equal to 1, as shown in Fig. 9.



(a) (b)

Fig. 8. Model training loss function curves when there is no artificial expansion of samples. (a) bounding box loss; (b) target category loss.



(a) (b)

Fig. 9. Model training loss function curves when adding artificial expansion samples. (a) bounding box loss; (b) target category loss.

E. Performance Evaluation and Error Analysis

In order to test the change detection effectiveness of our model, we conduct comparative experiments with traditional change detection methods, including Change Vector Analysis (CVA), traditional Object-Oriented Change Detection methods (OBCD), and Post-Categorization Comparison (PCC). At the same time, we compare with other image element-oriented deep learning methods, including MLP, CNN and LSTM). Their basic process is to merge the dual temporal phase images first, and then select a neighborhood of size 3×3 for each location pixel to get a vector of length 54 dimensions, which is input to the corresponding deep learning model for change detection.

V. Discussion and Prospect

In conclusion, while the results of this study provide valuable insights into the phenomenon being investigated, they are not without limitations and challenges. Understanding these limitations and addressing the associated challenges is crucial for advancing the field and building upon the findings of this study.

A. Limitations and Challenges of the Results of This Study

- The size and diversity of the dataset used in this study might have been limited, affecting the generalizability of the results. A larger and more representative sample would have provided a more comprehensive understanding of the phenomenon studied.
- The research methods employed might have had inherent constraints that affected the accuracy or reliability of the findings. For instance, certain assumptions made in the analytical framework might not have been fully met, leading to potential biases in the results.
- And the accuracy of the measurements used in this study might have been affected by various factors, such as instrument calibration or human error. This could have introduced noise into the data, making it difficult to interpret the results with certainty.
- At last the study might not have controlled for all relevant confounding variables, which could have influenced the observed relationships. The presence of such variables could have obscured true associations or led to spurious findings.

B. Suggestions and Prospects for Future Research

Based on the limitations and challenges identified in the previous section, this section outlines suggestions and prospects for future research in the area.

1) Suggestions for Future Research

- Expand Sample Size and Diversity. Future studies should aim to include a larger and more diverse sample to enhance the generalizability of the findings. This could involve collecting data from different geographical regions, cultural backgrounds, or population subgroups to capture a broader range of perspectives and experiences.

- Utilize Advanced Methodologies. Future research could explore the use of more advanced methodologies or analytical techniques to address the limitations of the current study. For example, longitudinal studies or experimental designs could provide stronger evidence for causal relationships.
- Improve Measurement Accuracy: Future studies should strive to improve the accuracy of measurements by using validated instruments, rigorous calibration procedures, and well-trained personnel [11]. This will help reduce measurement error and increase the reliability of the findings.
- Control for Confounding Variables: Future research should aim to control for all relevant confounding variables to ensure that the observed relationships are not obscured by external factors [12]. This could involve the use of statistical techniques such as regression analysis or structural equation modeling to account for potential confounding effects.

2) Prospects for future research

With the rapid development of deep learning, the associated problems in the use of various deep learning models will also be improved, and the future trend of deep learning is predicted according to the analysis in this paper [13–15].

- The model structure of a variety of algorithms is studied to improve the accuracy of remote sensing image processing and improve the ability of machine learning.
- The expansion of data samples is studied, and the sample size is increased in combination with various transformation forms of data processing to improve the accuracy of the model.

VI. Conclusion

This paper focuses on the target recognition and image change detection algorithms of remote sensing images based on deep learning. This paper first briefly introduces the traditional remote sensing image processing methods and the limitations of these algorithms. Then, the research progress of deep learning models in specific remote sensing applications is described, and the development, advantages and disadvantages of Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) models are analyzed and summarized. In this paper, we select datasets from Anhui Province and Hubei Province for comparative experiments to describe the data preprocessing, augmentation technology, training and optimization strategies, as well as the implementation process of target recognition and change detection in remote sensing images. Experimental setup, parameter adjustment, comparative experiments and results presentation, as well as performance evaluation and error analysis are described in detail. Finally, the "Discussion and Prospects" section highlights the limitations of this study, elaborates on the potential impact and value of the research results in practical applications, and looks forward to its future research directions.

Conflict of Interest

The author declares no conflict of interest.

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