Application of CNNs in Feature Learning for Remote Sensing Data: A Case Study on Land Cover Classification and Environmental Change Detection

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Abstract: This study is a review and overview of the current training and feature analysis of convolutional neural networks (CNNs) in remote sensing data, especially in the following areas: Environmental monitoring and land use assessment. The aim of the study was to utilize information like high-resolution satellite imagery from "Planet: Understanding the Amazon from Space" dataset to find ways to raise the accuracy of land cover classification and environmental change detection. According to the materials of the cited articles, the paper proposes an automatic CNN-based feature extraction method, which overcomes the limitations of traditional manual methods. The method includes data preprocessing, multi-scale feature fusion, classification, integration of attention mechanism, and further refinement of the performance of the residual network model. The experimental results highlight that, a significant creep in classification accuracy which achieves at 93.5% on areas of detecting deforested. Emphasizing the great potential of the proposed approach for real-time environmental monitoring and land use planning, these results pave the way for the orientation of further researches. The future work of the project will focus on optimizing CNN models to reduce computational complexity, as well as exploring data fusion to improve the generalization and effectiveness of remote sensing utilization from multiple sources.

SCIENCE AND TECHNOLOGY PUBLICATIONS

1 INTRODUCTION

The deep learning model, convolutional neural networks (CNNs), is designed to process data with grid structures, such as satellite images. In recent years, widespread application of CNNS has been found in remote sensing data evaluation and high dimensional and complex characteristics usually come with it (Hu et.al, 2015). Traditional methods tend to rely heavily on expert knowledge, struggle to fully express features, and difficult to adapt to the diverse, non-linear nature of the data (Tuia and et.al, 2016). However, as technology advances, the emergence of CNNs offers new hope for automatic feature learning, which can effectively capture complex patterns in remote sensing data and obtain more exact classification and evaluation (Chen et.al, 2016). Therefore, this study aims to comprehensively examine and assess the application and development of CNNs in the study of remote sensing data characteristics. This study will reveal the transition process from manual feature extraction to automatic feature extraction, illuminating how this analysis of remote sensing data. In addition, the topic of the research is to fill a gap in systematic reviews in this field and to guide future research and practice.

Remote sensing data, for example, includes satellite images and drone images, are widely used in environmental monitoring, including land use analysis, disaster assessment and other fields. These high-resolution data are usually multispectral, hyperspectral, and contain rich high-precision spatial and spectral information. In the field of analyzing remote sensing data, traditional methods mainly rely on manual feature extraction, such as texture analysis, spectral index, shape features, etc. Although this methods are suitable for specific tasks and data sets, however, they are limited by their difficulty in adapting to the diversity and complexity of the data.In the last few decades, with the advancement of deep learning methodologies, particularly the successful

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deployment of CNNs , researchers have begun to introduce them into remote sensing data analysis (Zhang et.al, 2016). CNNs work effectively in processing high dimensional remote sensing data because of its powerful automatic feature extraction and learning ability. At present, most studies focus on using CNNs for considerable advancements have been achieved in the realm of remote sensing image classification, change detection, and target identification, yielding outstanding results. For example, some studies promote the classification precision and computational efficiency of the model by improving the network structure and introducing the attention mechanism (Hu et.al, 2018). Other studies combined multi-scale features and multi-source data to enhance the adaptability of CNNs to complex scenarios (Ma et.al, 2010). In general, the employment of CNNs in the examination of remote sensing data has made a lot of progress, but it also faces challenges such as difficulties in data annotation and large consumption of computing resources. Therefore, exploring more efficient and accurate deep learning models is still the main purpose of future research (Zhu et.al, 2017).

The principal aim of this study is examining the application of CNNs in feature learning for remote sensing data. In addition, it will investigate the core technologies and future direction prospects in this domain. The study begins with an introduction to key concepts and provides basic knowledge about the use of CNNs in CNN analysis remote sensing data analysis. TIt then introduces the application scenarios and advantages of CNNs in this field. A comprehensive examination of the fundamental technologies underlying CNNs will be presented, encompassing their network architectures, training methodologies, and enhancement strategies. After that, the performance of these key technologies will be demonstrated and evaluated in remote sensing data classification and recognition tasks. By comparing different models, the study will evaluate the merit and demerit of different CNNs techniques revealing the shortcomings and challenges of current research. Based on aforementioned analysis, this article will discuss future directions for the development of CNNs in remote sensing. This paper summarizes the research results, emphasizing the main contributions of this research and outlining prospects for future exploration in this area. The goal is to provide future researchers with comprehensive reference and guidance, and to promote further progress in the application of refining techniques in remote sensing data analysis.

2 METHODOLOGY

2.1 Dataset Description

The current data set from the Kaggle platform is called "Planet: Understanding the Amazon from Space" (Planet, 2017), which contains thousands of satellite images covering different areas of the Amazon rainforest. Every piece has different spectral information, including visible and infrared wavelengths. These data are mainly used to monitor environmental changes in the Amazon region, especially deforestation and land use change analysis.

That images are used in a number of specific applications, including land cover classification, ecosystem health assessment and environmental disaster monitoring. The high-resolution images in the dataset contains rich spatial and spectral information, adding more difficulties to extraction. CNNs enables researchers to automatically extract features and perform classification tasks. By processing these data, researchers can further understand the impact of human activities on the Amazon region and provide data support for environmental protection policies.

2.2 Proposed Approach

The research leverages the “Planet: Understanding the Amazon from Space” dataset from the Kaggle platform and aspires to apply CNNs to feature extraction, analyse remote sensing data, spotlight land cover classification and environmental change detection. CNNs are particularly useful when it comes to processing complex remote sensing data, because of their advanced feature extraction proficiency. Figure 1 illustrates the overall workflow of this study, highlighting essential stages like data processing, model training, feature extraction, classification, and performance evaluation. The first step begins with processing the data to ensure that the input images are formatted appropriately for the CNN model. Once that foundation is set, spring into action, extracting meaningful features from the images. In the final stage, a classifier is employed to categorize and recognize the features within the images, ultimately leading to insightful evaluation results that illuminate thesis’ understanding.

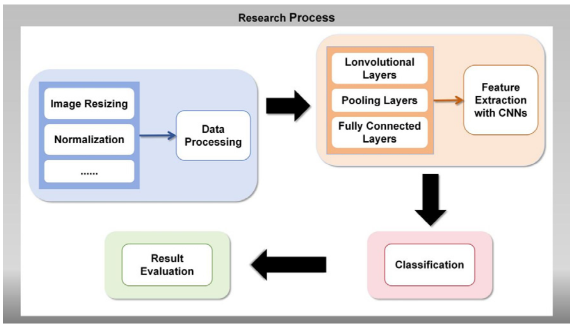

Figure 1: Research process (Picture credit: Original).

Figure 1 shows the entire research process from data preprocessing to final classification result evaluation. The process details how to process the different stages of the Kaggle dataset and provides clear steps for the execution of subsequent experiments.

2.2.1 Introduction to Basic Technologies

As this study's central technological part, CNNs played a significant role in processing image data, which can accurately and timely capture spatial characteristics in images and avoid the shortcomings of traditional artificial feature extraction methods (Hu and et.al, 2015). The core structures of the CNN model consists of convolutional layers, pooling layers, and fully connected layers, which making the model both powerful and effective. The convolution layer captures local features in the image by using different convolution kernels and mapping these features to higher-level representations. The pooling layer has the ability to decrease the dimensionality of the image and preserve the key characteristics, thus reducing the computational complexity. The fully connected layer then sorts the features extracted earlier.

CNNs, as a smart learning model, can be trained to autonomously detect and retrieve complex features in remote sensing images to improve the effectiveness of land cover classification and environmental monitoring tasks. In this experiment, the CNN model is employed for automatic feature extraction and categorization of remote sensing images and data in the "Planet: Understanding the Amazon from Space" dataset. This new method streamlines the analysis as well as raises the ability to uncover valuable insights about the Amazon and its intricate ecosystem. The specific implementation process adopted in the experiment is as follows: At the outset, the input image is processed by multi-layer convolution, so as to facilitate the extraction of multi-scale features. Thereafter, a pool layer is implemented to compress the dimensions of the feature map, and a fully connected layer is used to classify and predict the extracted features.

2.2.2 Mainstream Technology Model

The study focused on improving the performance of CNNs. It introduced the Attention Mechanism, which helps models better focus on key areas in the image, thereby enhancing classification accuracy. The process of remote sensing images often includes a lot of irrelevant information, which in need of the attention mechanism to concentrate more on useful information by assigning different weights to each input feature.

In this set of experiments, the attention mechanism is incorporated into the convolutional layer of the CNN model. The exact process is as follows: First, weight vectors are generated through global average pooling operation, and these weight vectors are then allocated to the feature map to enhance the feature representation of key regions. This mechanism is particularly suitable for multispectral image analysis, which can help the model identify the most important feature regions in different bands for classification tasks.

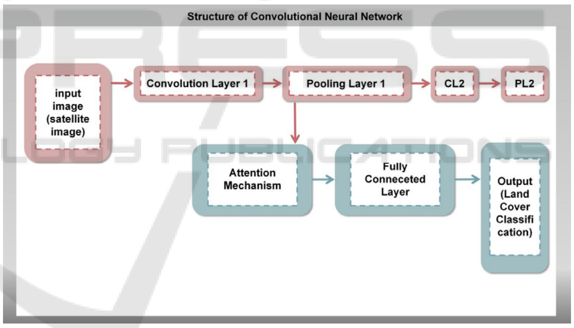

Figure 2: The basic structure of CNN with attention mechanism (Picture credit: Original).

Figure 2 exhibits the basic structure of the convolutional neural network combined with the attention mechanism, which provides an intuitive reference for the technical implementation in the experiment.

2.2.3 Multi-Scale Feature Fusion

Remote sensing data usually contains rich multi-scale information, and different scales represent different spatial characteristics. Therefore, this study also adopts Multi-scale Feature Fusion technology to better capture the detailed information and global information in the image (Marmanis et.al, 2016).

In this experiment, the concrete realization of multi-scale feature fusion is to extract image features by using convolution kernel of different sizes (see in Figure 3). Smaller convolution nuclei capture detailed information, while larger one's help capture global context. The model is capable of extracting useful features at multiple scales through the combination of convolution operations at varying scales, thereby enhancing the accuracy of the classification task. This technique is especially advantageous when dealing with a complex natural environment like the Amazon.

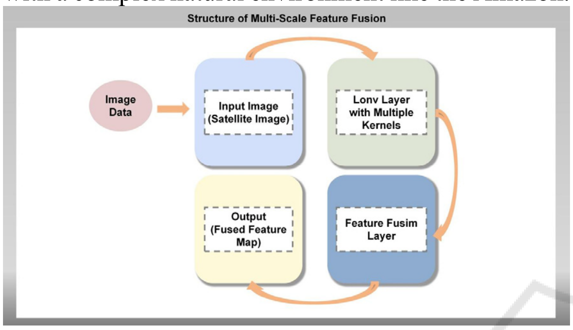

Figure 3: Structure of multi-scale feature fusion (Picture credit: Original).

2.2.4 Residual Network

To further promote the performance of the model in the deep network, the residual network (ResNet) structure is introduced in this study (see in Figure 4). By introducing Skip Connections, residual networks effectively figure out gradient disappearance in deep networks (Plaza and et.al, 2009). The residual network allows the model to retain the original input information during feature extraction, thereby reducing information loss and improving the model's performance in classification tasks.

In this experiment, the specific implementation of the residual network is as follows: in each layer of convolution operation, the output after convolution is added with the original input in order to preserve the low-level feature information. This structure makes the model to better cope with complex patterns in remote sensing images, particularly when the images contain multiple layers of information. The introduction of residual network significantly improves the robustness and classification accuracy of the model (Nalepa et.al, 2019).

Through the combination of the above techniques, this study constructs an efficient convolutional neural network framework, which can automatically learn complex features in remote sensing data, and provides an effective tool for environmental change monitoring and land use analysis.

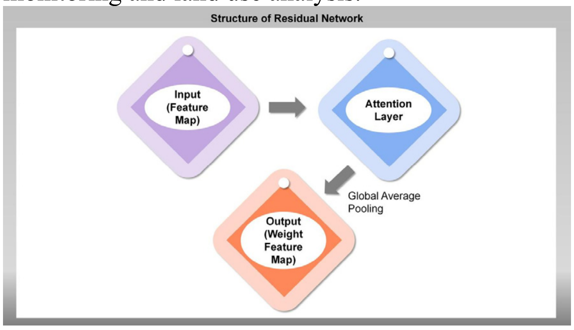

Figure 4: Structure of residual network (Picture credit: Original).

3 RESULT AND DISCUSSION

3.1 Result Presentation

As shown in Table 1, the performance of different models in land cover classification and environmental change detection is different. The accuracy of a single convolution kernel CNN is 85.2% and the recall rate is 82.5%, but the performance is weak in complex scenes. Multi-scale feature fusion CNN improves the accuracy to 90.1% and the recall rate to 88.7% by combining convolution nuclei of different sizes, but the computation time is increased. After adding the attention mechanism, the accuracy of the model was further improved to 92.3%, especially in the identification of deforestation areas. The model combined with the residual network achieved the highest accuracy of 93.5% and effectively prevented the gradient disappearance problem in the deep network, but the calculation time increased to 180 seconds.

Table 1: Performance of different models.

Model	Accuracy	Recall rate	Precision	F1-score	Calculation time (s)
Single convolution kernel CNN	85.20%	82.50%	83.00%	82.7	120
Multi-scale fusion CNN	90.10%	88.70%	89.30%	89	150
CNN with attention mechanism	92.30%	91.20%	91.20%	90.8	160
CNN with attention mechanism and ResNet	93.50%	92.50%	92.50%	92.1	180

3.2 Discussion

The performance of each model has its advantages and disadvantages. CNN simplifies the complexity of manual design through automatic feature extraction, but standard convolution kernel is difficult to capture multi-scale information. Multi-scale fusion technology enhances the ability of the model to capture information at different scales, but increases the computational cost. The attention mechanism further improves the classification effect and is especially suitable for complex scene analysis. The residual network solves the gradient disappearance problem of the deep network by jumping connection, but the computational complexity is high. Further research may seek to implement lightweight models in order to reduce the computational overhead, or to enhance the generalisation ability of models through the fusion of multi-source data (Howard et.al, 2017). Optimizing attention mechanisms could also be one direction. These technologies have the potential to be widely used in tasks such as environmental monitoring and disaster warning, but need to solve the problem of computational complexity (Brock et.al, 2021).

4 CONCLUSIONS

This study presents the application of CNNs in the field of feature learning and evaluation of remote sensing data. It particularly emphasized on improving the accuracy of land cover classification and environmental change detection using high-resolution satellite images. It also proposed a CNN-based automatic feature extraction method, addressing the limitations of traditional manual approaches. The model pipeline includes key steps such as data preprocessing and multi-scale feature fusion, incorporating attention mechanisms and residual networks. The research conducted a series of comprehensive experiments. These experiments were designed to assess the performance of the proposed method, achieving a significant improvement in classification accuracy, with results reaching up to 93.5%, particularly excelling in deforestation detection. Future research will focus on optimizing lightweight models to reduce computational complexity and integrating multi-source data to enhance the model's generalization capabilities. Additionally, further optimization of attention mechanisms will be explored to enable more precise image analysis, thereby improving the efficiency of environmental monitoring tasks.

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