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AI-Driven Change Detection in Satellite Imagery: Enhancing GIS Applications for Environmental Monitoring

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Abstract: Earth observation can also be supported by satellite imagery, but existing change detection techniques aren't very accurate and scalable for complex and heterogeneous landscapes. The goal of this paper is to propose an AI solution for the change detection with CNNs in satellite imagery. With the help of deep learning, the model can automatically detect complex, low-profile land-cover changes like urbanisation and deforestation, which isn't easily captured by other techniques. It was calibrated on high-resolution satellite images from NASA's Landsat and ESA's Sentinel missions, and used for a map of a region with dramatic land-use transformations over the past 10 years. These studies indicate that the AI-based approach is more accurate, more accurate and more reliable than other techniques such as image differencing. Also, AI is a way to combine with Geographic Information Systems (GIS) for live, automated monitoring, making environmental monitoring even more effective and flexible. The research shows how AI-based change detection can be used to increase the accuracy and timeliness of environmental monitoring, and provide new ways to actively take action in climate change, urban planning, and disaster management.

Keywords: AI-driven change detection, Convolutional Neural Networks, satellite imagery, GIS, environmental monitoring

1. Introduction

Environmental monitoring has long relied on satellite imagery to track changes in land cover and land use. Traditional methods of change detection, such as image differencing, Principal Component Analysis (PCA), and thresholding, have served as the foundation for these efforts. While computationally simple, these techniques often fail to provide accurate results, especially when dealing with complex and dynamic environments. Factors such as cloud cover, seasonal variations, and lighting conditions often interfere with the ability to detect true land-use changes, leading to misinterpretations in the results. This limitation is particularly evident in heterogeneous landscapes, such as urban-rural transitions or mixed-use regions, where traditional methods struggle to distinguish between actual changes and temporary environmental variations. To overcome these challenges, there has been a growing interest in incorporating artificial intelligence (AI) and machine learning techniques, particularly Convolutional Neural Networks (CNNs), into satellite image analysis. CNNs have proven highly effective in detecting spatial and temporal changes in satellite imagery, learning hierarchical features from raw data and automatically identifying patterns in complex images. Unlike traditional methods, CNNs can capture subtle and gradual changes in land cover, such as the

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expansion of urban areas or the deforestation of forests, that would otherwise be overlooked. Furthermore, AI-driven models can handle large-scale datasets, making them suitable for real-time monitoring applications. In this paper, the integration of AI with Geographic Information Systems (GIS) is explored as a means of improving the scalability and efficiency of environmental monitoring. GIS provides a platform for visualizing, mapping, and analyzing geospatial data, while AI algorithms can automate the detection of changes, eliminating the need for manual intervention [1]. By automating these tasks, AI-powered GIS systems can offer real-time updates, allowing decision-makers to act on the most current data. This paper specifically focuses on applying a CNN-based model to detect changes in land cover, such as urbanization and deforestation, in a region that has undergone significant changes over the past decade. The results are compared to traditional change detection methods to demonstrate the improvements in accuracy, precision, and computational efficiency achieved by AI-based solutions.

2. Literature Review

2.1. Traditional Change Detection Methods

Some traditional change detection techniques for satellite images are image differencing, principal component analysis (PCA) and thresholding. Such techniques evaluate images against each other to spot differences — image differencing looks for big differences between pixels in two pictures. The computations are easy, but the method fails to cope with changes in seasons, cloud cover, lighting conditions, and give a false positive. They're also not very efficient with big, noisy data or heterogeneous environments, so aren't very useful for tracking small or gradual trends. These limitations have led to the development of newer, automated ways to detect changes with a greater accuracy and scalability [2].

2.2. Deep Learning in Change Detection

Deep learning, specifically Convolutional Neural Networks (CNNs), have been very helpful for change detection in satellite image. CNNs can automatically learn features based on the raw pixel information and recognize changes over space and time, so they are good for tracking land-cover change (urbanisation or forest clearing) [3]. CNNs can work on big data, and learn from any kind of environmental variation compared to the previous methods. Yet it still has issues with large labeled datasets for training and computational power, in large, mixed regions at least.

2.3. Integration of AI with GIS for Environmental Monitoring

Combining AI and Geographic Information Systems (GIS) helps in environmental monitoring by automating the analysis of satellite images. The algorithms in AI are now able to better detect and track land cover changes, urban development, and forest clearing as they happen. This combination allows GIS platforms to crunch big amounts of data with real-time updates to aid decision-making. AI-powered GIS solutions are scalable and capable of tracking large scale, especially for environmental monitoring at a scale that's global in nature, as well as climate change and biodiversity loss [4].

3. Methodology

3.1. Data Acquisition

Satellite data for this research was culled from public datasets from NASA's Landsat program and the European Space Agency's (ESA) Sentinel mission. These satellites have high resolution images that are time-stable enough to measure long-term environmental trends. The 30 metre and 10-20 meter resolution of Landsat and Sentinel-2 allow you to track changes in the land cover, and therefore they can be used to track deforestation, urbanisation and agriculture.

In this experiment, we used a region that had experienced major land-use change in the past 10 years. The chosen region includes urban and rural areas where accelerated urbanisation and logging have been especially evident. We examined these shifts with satellite data from two years ago: 2015 and 2020. Both images were chosen to cover five years, so that we could contrast land cover changes. Before any change detection actually happened, the images collected were preprocessed to smoothen the image and provide a precise analysis. These preprocessing steps were atmospheric correction, where the weather – cloudiness, fog, etc. – can corrupt satellite data. Also we did geometric correction to coordinate the images spatially (as to register the different dates). This step is important as even small asymmetry between the images causes faulty change detection. Further, the images were resampled at the same spatial resolution so that the images did not change across the dataset [5]. These preprocessed images were the result of these preprocessing steps, and they were now spatially aligned images that could be analysed. Table 1 plots quantitative breakdowns of the land cover categories, as proportions of urban, forest, agricultural and watershed land, over both time periods.

Table 1: Land Cover Distribution in 2015 and 2020

Land Cover Type	2015 Area (sq. km)	2020 Area (sq. km)	Change (sq. km)	Percentage Change (%)
Urban Areas	120	180	+60	+50
Forests	400	320	-80	-20
Agricultural Land	350	370	+20	+5.7
Water Bodies	50	50	0	0

3.2. Model Architecture

This paper used a CNN to detect chang, a pre-trained VGG16 model that was trimmed to the dataset properties. VGG16, originally developed for image classification, is popular for deep architecture and the extraction of hierarchical features from pictures. To detect change, the model had to learn and discriminate between change and non-change regions between satellite images. Our chosen model was VGG16, which is well-known for spatial pattern recognition and its adaptability in transfer learning – weights of an already trained model can be optimized for a new dataset.

The CNN model we employed in this work had a supervised learning technique with training data from satellite images and associated labeled ground truth data. These ground truths were pixels manually labelled with places where significant transitions had taken place over two time-horizons. These labeled regions offered the model the oversight needed to train it on the properties that separate transformed regions from unchanged [6]. Its training data had been carefully constructed to cover the wide range of land-use changes (urban development, clearing forests, agricultural conversion) to ensure that the model could be generalised across all such land-use transformations. The model was optimized using the Adam optimizer which is commonly used for deep learning training because of its fast learning speed and performance on large data. It settled for a learning rate of 0.0001 to avoid fast convergence without going over the bounds of optimality. The batch size was 32 — this is the usual, good-sized number for a training speed and memory usage that balances. This last layer in CNN structure was adjusted to create a binary classification map. All the pixels in the final map were either "changed" (with a value of 1) or "unchanged" (with a value of 0), depending on what the learned features were. This dichotomous division allowed pinpointing regions where major developments

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had taken place in the two time periods. We tested the architecture of the model (which combines VGG16's feature extraction along with a final classification layer for change detection) against a test set of pair-to-pair satellite image pairs not trained on. The model performance was measured by standard measures like accuracy, precision, recall and F1 score [7]. Table 2 shows the numerical results of how well the model has done under various land-cover change scenarios. These findings give a measure of how well the model was able to catch different forms of environmental change, such as urbanisation, clearing forests and land development.

Table 2: Performance of CNN Model in Change Detection

Change Type	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Urbanization	92.4	91.5	93.2	92.3
Deforestation	88.1	85.7	89.5	87.6
Agricultural Expansion	90.3	89.2	91.7	90.4
Overall	90.3	88.8	91.5	90.1

3.3. Evaluation Metrics

A variety of commonly used measures – accuracy, precision, recall, F1-score – were applied to analyse the effectiveness of the AI-based change detection model. These parameters help understand different features of the model's detection and classification of satellite image changes. The easiest of these is accuracy — the percent of correctly detected pixels (both altered and unaltered). It is the sum of correct predictions (true positives and true negatives) divided by the number of pixels in the image. Yet precision and recall are more subtle ratings when datasets are unbalanced or the cost of false positives and false negatives is unbalanced. This is where accuracy is the fact that the model can be used to detect changed pixels, without mistakenly marking changed regions as unchanged. It's calculated as the ratio of true positives (properly detected changes) to all pixels labelled changed (true positives + false positives). Recall (or sensitivity) refers to the model's detection of all real change with as little false negatives as possible. It is equal to the sum of the number of positives to the number of real-world changes (positives minus negatives). F1-score is the performance metric (which balances accuracy and recall). It is the harmonic middle between precision and recall, providing only one measure which penalises high precision or recall values. The formula for F1-score is:

$$\text{F1-score}=2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{1}$$

In addition to these metrics, this paper compared the performance of the Al-driven model with traditional change detection techniques, such as image differencing, to evaluate improvements in automation and accuracy. Image differencing, while useful for detecting gross changes, often struggles with subtle or complex alterations in land cover [8]. By comparing the F1-scores and other metrics of the Al-driven model against the traditional methods, it became evident that the Al model provided superior detection capabilities, especially in regions with heterogeneous landscapes or mixed land-use changes. This demonstrated that Al-driven models can significantly enhance both the speed and accuracy of change detection processes.

4. Experimental Results

4.1. Model Performance

The artificial intelligence model was much better than the traditional method at identifying satellite image change detection. The CNN had an overall precision of 92% which is a lot better than the older image differencing method, which was only 78%. Not only the accuracy, but the CNN model had a

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precision of 91% and a recall of 93%. These numbers are a measure of how much the model was able to predict changes in real time (precision) and have a good probability of getting every real change right (recall). Our F1-score (for precision and recall) was set to 0.92 which also shows that the model had a good equilibrium in detection of actual changes and zero false positives or false negatives. Comparing the old image differencing method with the CNN model, it was easy to see that the CNN model spied more real-world variations. The more basic and fast option of image differencing was often unsuited to pick up on small variations or small environmental changes, because pixel value subtraction could be subject to noise, seasonal variation or cloud cover. This CNN-model and the conventional approaches perform better (see Table 3, accuracy and F1-score for CNN model are much higher). This comparison shows the clear advantage of CNN for change detection in large and noisy systems [9]. Because the AI model can learn spatial patterns and spatial correspondences between pixels, it's able to adapt to different kinds of changes in the environment much better than any traditional approach.

Table 3: Comparison of Model Performance

Metric	CNN Model	Image Differencing
Accuracy (%)	92	78
Precision (%)	91	74
Recall (%)	93	76
F1-score	0.92	0.74

4.2. Change Detection Accuracy

The model was highly effective in detecting all land-use transformations including deforestation and urbanization. The CNN model was also quite precise for deforestation with 94% accuracy, predicting areas where the forest had lapsed in recent times. This accuracy was due in large part to the model learning features deep from the satellite imagery and distinguishing vegetation decline areas from natural variability like seasons. Urbanisation was slightly less accurate, 89%, but a much better result than using traditional image differencing that generally couldn't show slow, incremental transformations. The CNN model could detect urbanisation into former farm or rural territory, an under-recognised but important shift that is not easily detected by other approaches. Here the spatial resolution and the precision of the AI model played a major role (especially in planning and monitoring applications). In both deforestation and urbanization detection cases, CNN beat image differencing as outlined in Table 4. Traditional techniques picked up on the most dramatic, massive changes, but they didn't pick up on the more incremental, slow-moving changes to the landscape [10]. AI-powered methods, however, showed they could detect such subtle shifts, which are typically important to environmental monitoring and city planning.

Table 4: Change Detection Accuracy for Deforestation and Urbanization

Change Type	CNN Model Accuracy (%)	Image Differencing Accuracy (%)
Deforestation	94	78
Urbanization	89	75

5. Conclusion

This study demonstrates the significant advantages of using AI-driven change detection models, particularly Convolutional Neural Networks (CNNs), for satellite imagery analysis in environmental monitoring. The results show that the CNN model outperforms traditional methods like image differencing in detecting subtle and complex changes in land cover, such as deforestation and

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urbanization. The accuracy, precision, and recall metrics for the CNN-based model are notably higher, highlighting its ability to capture real-world changes with greater reliability. Moreover, the integration of AI with Geographic Information Systems (GIS) further enhances the scalability and efficiency of the monitoring process. By automating change detection and real-time updates, AI-powered GIS systems can support proactive decision-making in fields such as climate change, urban planning, and disaster management. The ability of deep learning models to process large datasets quickly and accurately opens new possibilities for environmental monitoring. However, challenges remain, particularly in terms of data availability, model interpretability, and the computational resources required for training and deployment. Despite these challenges, the promising results of this study suggest that AI-driven change detection will play an increasingly important role in the future of environmental monitoring, providing more accurate, timely, and scalable solutions for addressing global environmental issues. Further research into improving model training, interpretability, and application to diverse environmental contexts will be crucial in realizing the full potential of AI in this field.

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