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Change Detection in Road Networks During Conflicts: A Deep Learning Framework with Aerial Photography

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A B S T R A C T

Monitoring transformations in road infrastructure is critical for disaster response and recovery in conflict regions. However, manual analysis of road damage is time-consuming and limited in scale, while the speed of changes requires near real-time monitoring. This paper presents a deep learning framework using Hybrid Spectral Networks (HybridSN) for change detection in road networks during conflicts, applied to the city of Old Mosul, Iraq. The HybridSN model achieved high accuracy in road detection, with recall of 0.990 in 2014 and 0.982 in 2022. Change detection analysis revealed a substantial reduction of 13,249.83 m in total road length from 20,186.93 m in 2014 to 6,937.10 m in 2022, indicating widespread damage. The quantitative results demonstrate the capabilities of the proposed approach in assessing road network changes through conflict.

1. Introduction

In regions affected by conflicts, the integrity of road networks can undergo significant transformations due to various human activities, including warfare and displacement. These transformations not only pose immediate safety concerns for civilians but also have profound implications for post-conflict recovery and reconstruction efforts. Monitoring and comprehensively assessing these changes in road networks during conflicts are paramount for disaster management, urban planning, and humanitarian interventions [1]. However, the sheer scale and complexity of such assessments present significant challenges.

Traditional manual methods of monitoring and cataloging changes in road infrastructure are time-consuming, labor-intensive, and often error-prone, especially in conflict zones where access can be restricted or dangerous. Furthermore, the speed at which these changes occur demands real-time or near-real-time monitoring, which is practically unattainable with conventional techniques.

To address these challenges, this research focuses on the development and implementation of an advanced deep learning framework, utilizing high-resolution aerial photography as the primary data source [2]. The primary goal is to create a robust system capable of automating the detection and assessment of changes in road networks during conflicts with a high degree of accuracy and efficiency.

This research paper presents a comprehensive investigation into the detection of changes in road infrastructure during conflicts using a state-of-the-art deep learning framework and aerial photography. The subsequent sections detail the methodology and findings of this study. The core of the proposed approach lies in the development of a robust road detection model, employing Hybrid Spectral Networks (HybridSN) for improved accuracy. The research presents the proposed model, which combines the strengths of these deep learning techniques to accurately identify road networks in high-resolution aerial photographs. Subsequently, the paper delves into the critical aspect of change detection, highlighting the methods employed to identify alterations in the road infrastructure over time. To assess the model's performance, the study employs various evaluation methods, providing a thorough analysis of the results. Finally, the paper concludes by summarizing the key takeaways and contributions of this research. The study contributes to the field of change detection in road networks during conflicts, offering a robust deep learning framework that can be applied to similar regions worldwide. This research aims to provide valuable insights for policymakers, urban planners, and humanitarian organizations involved in conflict-affected areas.

2. Literature Review

The realm of remote sensing has been revolutionized by the emergence of deep learning techniques, offering powerful tools for detecting changes in aerial and satellite imagery [3]. Traditionally, remote sensing analysis relied heavily on manually engineered feature extraction and shallow machine learning models. However, with the proliferation of large-scale remote sensing datasets, there is a growing need for more automated and scalable approaches [4-6]. Deep learning has risen to the challenge, demonstrating remarkable success in various fields, including computer vision. In recent years, the application of deep learning to remote sensing data analysis has yielded state-of-the-art results across multiple tasks.

Deep learning models, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs), have found relevance in remote sensing tasks [7-12].CNNs excel in 2D imagery analysis, capturing spatial relationships and features effectively through convolutional layers. RNNs are adept at handling sequence data, making them valuable for temporal analysis of satellite data streams. GANs, on the other hand, have been instrumental in generating realistic synthetic imagery, contributing to data augmentation and reconstruction efforts.

One of the primary applications of deep learning in remote sensing is change detection, a task with wide-ranging implications. For instance, [13] evaluated various pretrained CNN models for multiclass land cover classification using satellite images, achieving remarkable accuracy with ResNet50, which outperformed traditional machine learning approaches. [14] focused on building recognition and segmentation from high-resolution satellite images, achieving state-of-the-art results with a modified U-Net architecture. [15] validated deep CNNs for land cover classification, with the ResNet model performing exceptionally well. [16] introduced an unsupervised deep feature learning framework, confirming competitive performance on downstream classification tasks without label supervision.

These studies collectively highlight the adaptability and effectiveness of deep CNNs in diverse remote sensing tasks, including change detection. Deep learning models outperform traditional approaches, offering the ability to extract meaningful features directly from raw satellite data without extensive feature engineering. Moreover, they are capable of capturing multi-scale contextual relationships, a crucial advantage in remote sensing applications. As remote sensing data continues to grow in volume and complexity, deep learning stands as a crucial tool for effectively harnessing these resources.

Accurate change detection in urban environments, particularly from aerial and satellite imagery, is vital for applications ranging from urban planning to disaster management [17,18]. Traditional methods for change detection often relied on manually crafted features and shallow machine learning models, presenting limitations when dealing with intricate and diverse urban landscapes. With the ascent of deep learning, CNNs have emerged as powerful tools for change detection in remotely sensed imagery [11,19]. CNNs excel by learning hierarchical feature representations directly from raw pixel data.

Several CNN architectures have been specifically tailored for change detection, including models that combine local and global context for road detection [20]. Others have introduced multistage frameworks for joint extraction of different urban features or incorporated directional attention and geographic features for improved topological continuity [21]. The introduction of squeeze-and-excitation blocks has further enhanced feature map recalibration [22]. These developments have consistently set new benchmarks in change detection, reinforcing the benefits of specialized deep CNNs.

Despite notable progress, challenges persist in the realm of change detection. These challenges include the identification of small, occluded, or low-contrast changes, complexities arising from urban environments with shadows, overpasses, and dense buildings, as well as the need for generalization across diverse geographic areas. Ongoing research efforts focus on improving deep neural networks, harnessing large, annotated datasets, and leveraging synthetic data to address these limitations, promising enhanced change detection capabilities.

The literature reviewed emphasizes the transformative potential of deep learning in the field of change detection in remote sensing, particularly in urban environments. Deep learning models, notably CNNs, have showcased their adaptability and effectiveness in extracting meaningful features and capturing complex contextual information directly from raw imagery. As remote sensing data continues to expand in scale and complexity, deep learning remains poised as a vital tool for the effective analysis of these resources, offering solutions to long-standing challenges in change detection and urban feature extraction.

3. Methodology

Old Mosul, situated in the Nineveh Governorate of northern Iraq, is a city with a profound historical and cultural legacy as Fig. 1. Its roots trace back thousands of years, making it one of the world's oldest continually inhabited areas. The city's significance lies not only in its age but also in its architectural diversity, influenced by numerous civilizations that have ruled the region for centuries. Within Old Mosul, one can find an array of historical treasures, including ancient mosques, churches, and traditional dwellings, all reflecting the city's rich history.

Regrettably, Old Mosul has faced significant challenges in recent years, notably during the battle to liberate the city from ISIS in 2017 [23]. This conflict resulted in extensive damage to its historic buildings and infrastructure. However, the city's resilience and determination shine through ongoing reconstruction efforts, with the support of organizations like UNESCO and UNDP, aiming to restore and preserve its unique cultural and historical heritage [24].

Despite the adversity it has faced, Old Mosul continues to attract tourists and scholars eager to explore its captivating past and witness the ongoing revitalization of this extraordinary city. It stands as a testament to the enduring spirit of its people and the importance of safeguarding cultural heritage in the face of adversity. The data used in this study were collected from a variety of sources Table 1 .

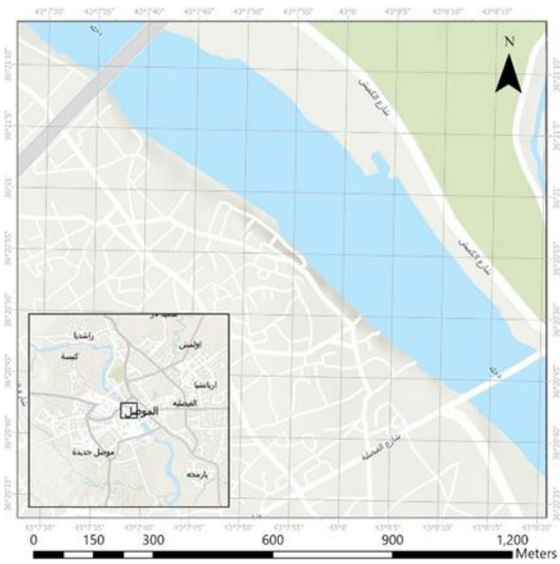

Fig. 1. Location of the study area – the city of Old Mosul.

Table 1. List of data used in this study were collected from a variety of sources.

Data	Acquisition Date	Spatial Resolution	Source	Application
UAV photos	2023	5472x3648 pixels	DJI Phantom Pro UAV system	Classification
Aerial photos	2009	0.1 m	State Commission Of Survey	Classification
GPS control points	2023	0.003 m	DGPS	Geometric calibration
DEM	2022	3 m	State Commission Of Survey	3D modelling

The initial steps in the data preparation involve the preprocessing of raw aerial imagery and corresponding ground truth masks. This process ensures that the data is suitably formatted and scaled for subsequent model training and evaluation. Then, the process commenced by loading the raw aerial imagery and ground truth masks using the Rasterio library. To facilitate consistent model processing, we normalize the pixel values by dividing them by the maximum pixel value, effectively rescaling them to a range between 0 and 1. Next, we address the challenge of extracting patches from the imagery and masks for model training. To achieve this, we employ a sliding window approach, where a fixed-size window traverses the images. To enable patch extraction at image borders, we introduce a margin through zero-padding.

In the interest of achieving dense coverage and robust feature learning, we sampled patches with a 50% overlap between adjacent patches. The patch size, empirically determined through model performance evaluation, is set to 3x3 pixels. This choice allows the CNNs to focus on local textures and patterns, contributing to effective road/background differentiation. To tackle class imbalance, a common issue in road detection tasks where road patches are far outnumbered by background patches, we implement random oversampling for the road class. This oversampling technique augments the number of road patches to balance the dataset, ensuring that both road and background patches are sufficiently represented. Subsequently, the number of background patches is subsampled to align with the oversampled road patches, maintaining dataset consistency. The sampled patches, along with their corresponding binary road/background labels, are then concatenated into tensors, preparing the data for model training and evaluation. To facilitate the model's classification task, we apply categorical conversion to transform the binary labels into one-hot encoded labels.

Deep learning is a subset of machine learning that focuses on neural networks with many layers, known as deep neural networks. It has gained immense popularity due to its ability to automatically learn representations from data, enabling it to excel in a wide range of tasks, including image recognition, natural language processing, and spatial data analysis.

At the core of deep learning are artificial neural networks, which are inspired by the structure and function of biological neurons. A neural network consists of layers of interconnected nodes (neurons) that process and transform data. The input layer receives data, and subsequent hidden layers learn progressively abstract representations of the input. The output layer produces the final prediction or classification. Activation functions introduce non-linearity into neural networks, allowing them to model complex relationships in data. Common activation functions include ReLU (Rectified Linear Unit), sigmoid, and tanh. They determine the output of each neuron based on its input. In a feedforward neural network, information flows from the input layer through the hidden layers to the output layer. Backpropagation is the process of updating the network's weights and biases to minimize the difference between predicted and actual outputs. This optimization technique uses gradient descent to iteratively adjust the network's parameters.

Deep learning has made significant contributions to spatial data analysis by leveraging its ability to extract complex patterns and representations from geospatial datasets. CNNs are used to classify satellite and aerial images for land cover classification, urban planning, and disaster monitoring. They can distinguish between different types of terrain, vegetation, and built-up areas with high accuracy.

Convolutional Neural Networks have revolutionized image analysis tasks due to their ability to learn hierarchical features from data, making them particularly well-suited for tasks like object recognition and image classification. In the context of road detection, CNNs are employed to automatically extract discriminative features from aerial photographs.

CNNs consist of multiple layers, including convolutional layers that apply filters to input data, pooling layers that downsample feature maps, and fully connected layers for classification. For our road detection task, we adapt a pre-trained CNN architecture, fine-tuning it to recognize road features in aerial images.

The HybridSN model embodies a sophisticated convolutional neural network architecture that adeptly processes both spectral and spatial features to facilitate road extraction from aerial imagery as Fig. 2. The input data comprises 3D patches, encompassing 2D spatial regions and 1D spectral signatures. This integration of spectral and spatial information is pivotal for the accurate detection of roads in diverse and complex imagery.

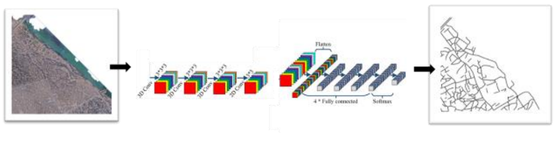

Fig. 2. HyrbidSN architecture.

The HybridSN model consists of several core components, beginning with 3D convolutional layers that learn both spectral and spatial features simultaneously. These are followed by a reshaping of the feature maps into a 2D format to preserve the integration of spectral and spatial information. A 2D convolutional layer is then applied to further enhance spectral fusion. The features are flattened into a 1D vector and passed through two dense layers with 32 and 16 units, respectively, both using ReLU activation to capture higher-level representations for distinguishing roads from their surroundings. Dropout regularization with a rate of 0.4 is applied after each dense layer to reduce overfitting and improve generalization. The final softmax layer outputs probabilities indicating the likelihood of each pixel belonging to the road class. The model is trained end-to-end using the Adam optimizer and categorical cross-entropy loss, making HybridSN a powerful tool for road detection, especially in monitoring changes during urban conflicts.

Change detection plays a crucial role in the research methodology, focusing on identifying changes in road infrastructure over time, especially in conflict-affected areas. The HybridSN model is utilized to strengthen this process. The approach involves using image differencing techniques by subtracting pixel values from aerial images taken at different times to detect changes. This includes pixel-wise differencing to create maps of change and thresholding to classify areas as changed or unchanged. The HybridSN model is central to detecting road changes, as it is used to extract road networks from aerial images, resulting in binary masks that show where roads exist. These masks are then compared across time using differencing methods to identify significant changes in road structures. The detected changes are analyzed based on their area and geometry, offering insights into how road networks evolve in response to conflict-related events.

The effectiveness of our change detection approach, employing the HybridSN model and image differencing techniques, is evaluated through a comprehensive set of assessment methods. These methods provide a multifaceted view of the performance of our model and its ability to accurately detect changes in road infrastructure during conflicts.Overall accuracy is a fundamental evaluation metric that measures the proportion of correctly classified pixels in the change detection results. It provides a holistic view of the model's ability to correctly identify both changed and unchanged road segments, giving an overall assessment of accuracy. The Kappa index, also known as Cohen's Kappa, is a statistical measure that evaluates the agreement between the predicted change detection results and ground truth data while accounting for chance agreement. It provides a robust measure of classification accuracy, considering both true positive and true negative classifications. The F1-score is a metric that balances precision and recall, making it particularly useful when dealing with imbalanced datasets. It measures the harmonic mean of precision and recall, providing insights into the model's ability to accurately detect changes while minimizing false positives and false negatives. Recall, also known as sensitivity or true positive rate, quantifies the proportion of actual changes that the model correctly identifies. It is a crucial metric for assessing the model's ability to capture all instances of changes in road infrastructure. Precision measures the proportion of correctly detected changes out of all changes identified by the model. It helps evaluate the model's accuracy in change detection while minimizing false positives. Intersection over Union (IoU): IoU, also known as the Jaccard Index, assesses the spatial overlap between the predicted change detection results and ground truth data. It provides a measure of how well the model's detected changes align with the actual changes, considering both false positives and false negatives.

4. Results and Discussions

The HybridSN model was developed and used to detect roads in aerial photographs over the study area in 2014 and 2022. The aerial photograph of 2014 was used to reflect the city environment before the conflict, while the aerial photograph of 2022 was used to detect the recent destructions in roads due to the conflict. The classification model was used to detect the roads in both years. Fig. 3. shows the maps of the detected roads.

The accuracy assessment presented in Table 2 presents the following observations about using the HybridSN model for road detection in aerial photographs. First, the overall accuracy (OA) and kappa coefficient increased from the 2014 to 2022 version of the HybridSN model, indicating improved overall performance in correctly classifying pixels as road or non-road. The recall for the road class is high for both models (0.990 and 0.982), meaning the models are able to correctly identify most of the road pixels in the images. However, the precision and IoU are higher for the 2014 model.

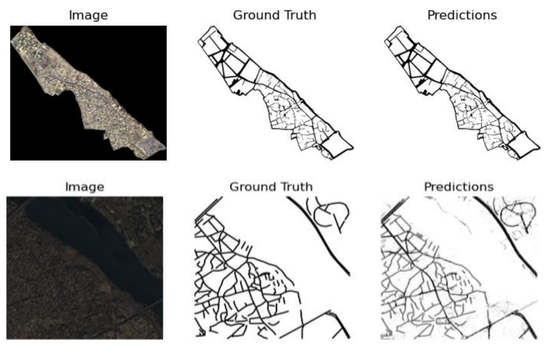

Fig. 3. Results of road detection by the HybridSN model for 2014 (above) and 2022 (below).

The precision, F1-score, and IoU are lower for the 2022 model compared to 2014, suggesting that while the 2022 model improved at detecting roads (higher recall), it had more false positives leading to lower precision and IoU. The decrease in precision and IoU indicates the 2022 model is less able to differentiate road vs non-road pixels, even though overall accuracy increased. This could be due to overfitting or imbalanced training data.

The road detection in 2014 and 2022 enabled the change analysis of the roads in the city due to the recent conflict. The maps of the road detection in the two years were used to create the change map as Fig. 4. The map shows the roads before and after the conflict. As a results, the total lengths of the roads in the two period were calculated and analyzed Table 3.

The total length of detected roads in the old city of Mosul decreased substantially from 20,186.93 m in 2014 to 6,937.10 m in 2022, a difference of 13,249.83 m Table 3. This large reduction in total road length can be attributed to the destruction and obliteration of roads resulting from the conflict and intense urban warfare that occurred in Mosul between 2014 and 2017.

Table 2. Accuracy assessment of the Hybrid SN model for road extraction.

Hybrid 2022	Hybrid 2014	Model
0.969	0.933	OA
0.875	0.948	Kappa
0.982	0.990	Recall
0.806	0.990	Precision
0.885	0.950	F1-score
0.806	0.990	IoU

Our change detection analysis revealed extensive damage and elimination of roads across the old city during this period. Numerous roads were found blocked by debris, demolished buildings, or purposeful barricades.

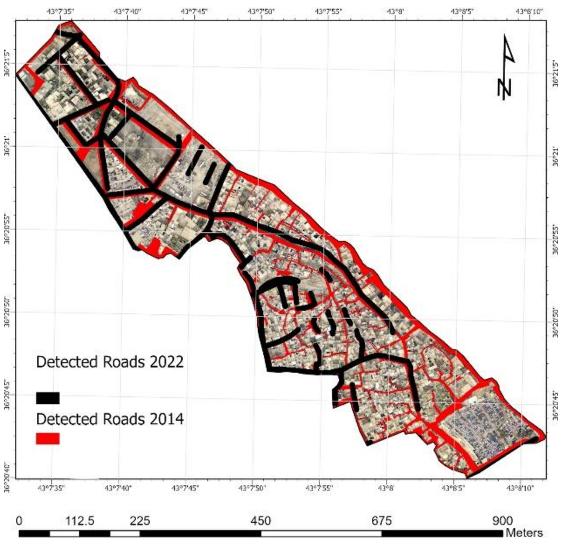

Fig. 4. Map of the change detection in roads in the study area due to the recent conflict.

Main thoroughfares and side streets alike were disrupted by the effects of artillery strikes, air raids, and street-level fighting. These damages severely interrupted the connectivity and continuity of the road network in Mosul's urban core. The scale of road length reduction, comprising almost two-thirds of the 2014 total length, provides quantitative evidence of the widespread devastation to transportation infrastructure. Given the importance of roads for mobility, supply lines, and civilian access across any urban area, our results highlight the long-term impacts of conflict on the old city's morphology and accessibility. The truncation of roads impedes the ability of residents and services to navigate across neighborhoods in the post-conflict environment.

Targeted efforts to re-establish disrupted roads and reconnect isolated areas will be crucial for rebuilding and recovery in Mosul. The data provided by this change analysis allow identification of the most damaged areas to direct road repair and reconstruction priorities

Table 3. The total lengths of the roads and their difference between 2014 and 2022.

Year	Total Road Length (m)
2014	20186.93
2022	6937.10
Difference	13,249.83 (65%)

5. Conclusions

The HybridSN model developed in this study integrates spectral and spatial information to accurately detect roads in diverse aerial imagery. The inclusion of spectral signatures alongside spatial context enables robust discrimination between roads and background regions. The model architecture applies specialized 3D convolutional layers for joint spectral-spatial feature learning, followed by reshaping and further convolutional processing for enhanced feature fusion. The model achieved high road detection accuracy in both 2014 and 2022 imagery. However, precision and IoU were lower in 2022, suggesting increased false positives despite higher overall accuracy.

The change detection analysis revealed a major reduction of 13,249.83 m in total road length from before to after the conflict. This large-scale damage to roads is indicative of the severe impacts of urban warfare on transportation infrastructure connectivity and accessibility. The results provide quantitative evidence of extensive road network disruption, with implications for mobility and civilian access during recovery. Targeted reconstruction efforts guided by the change detection data could help reconnect isolated areas and restore access across the city.

This research demonstrates the potential of a deep learning approach using HybridSN for assessing changes to road networks in conflict regions. The model provides accurate road detection, while change analysis quantifies infrastructure damage. The framework was validated on aerial images of Mosul, Iraq, revealing a 65% reduction in road length from extensive conflict-related destruction. The study provides an automated tool to guide reconstruction and highlights the utility of deep learning with spectral-spatial data fusion for change detection tasks. Key contributions include the specialized HybridSN architecture and quantitative documentation of road damage. Further work can expand this approach to additional conflict zones worldwide.

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