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Deep Learning-Based Deforestation Detection in the Mountainous Region of Da Nang, Vietnam, Using Sentinel-2 Remote Sensing Data

Phát hiện khu vực mất rừng dựa trên học sâu sử dụng dữ liệu viễn thám Sentinel-2 ở khu vực miền núi tại Đà Nẵng, Việt Nam

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Abstract

This study employs a convolutional neural network (CNN) to detect deforestation from Sentinel-2 true-color imagery in mountainous areas of Da Nang, Vietnam. Image patches of 256×256 pixels were extracted from median-filtered Sentinel-2 composites and classified into two groups: intact forest and deforestation. A total of 280 samples (140 per class) were prepared, of which 200 were used for training, 40 for validation, and 40 for testing. Data augmentation via horizontal and vertical flipping was applied to the training set to increase sample diversity. The results indicate that the CNN architecture with 3 convolutional layers is well suited for the task at hand. The deep learning model achieved an overall accuracy of 93% on the test set. For images classified as deforestation, subsequent image segmentation was used to estimate the proportion of non-forest pixels. The findings demonstrate the strong potential of deep learning and image processing for monitoring forests in mountainous regions.

Keywords: convolutional neural network, deforestation detection, remote sensing, Sentinel-2 imagery, forest management

Tóm tắt

Nghiên cứu này sử dụng mạng nơ-ron tích chập (CNN) để phát hiện khu vực suy giảm diện tích rừng từ ảnh Sentinel-2 với tổ hợp màu thật tại các khu vực miền núi tại Đà Nẵng, Việt Nam. Các mẫu ảnh với kích thước 256×256 pixel được trích xuất từ ảnh Sentinel-2 xử lý với bộ lọc trung vị và được phân thành hai nhóm: rừng nguyên vẹn và mất rừng. Tổng cộng có 280 mẫu (140 mẫu cho mỗi lớp) được xây dựng, trong đó 200 mẫu dùng để huấn luyện, 40 mẫu để kiểm định và 40 mẫu để kiểm tra. Sự tăng cường dữ liệu cho ảnh với phương pháp lật ngang và lật dọc được áp dụng cho tập huấn luyện nhằm tăng tính đa dạng của mẫu. Kết quả cho thấy kiến trúc CNN với 3 lớp tích chập phù hợp với bộ dữ liệu đã thu thập. Mô hình học sâu đạt độ chính xác tổng thể 93% trên tập kiểm tra. Đối với các ảnh được phân loại là mất rừng, thuật toán phân cụm được sử dụng để ước lượng tỷ lệ điểm ảnh không có rừng. Các kết quả này cho thấy tiềm năng lớn của học sâu và xử lý ảnh trong việc giám sát rừng ở vùng núi.

Từ khóa: mạng nơ-ron tích chập, suy giảm độ che phủ rừng, viễn thám, ảnh vệ tinh Sentinel-2, quản lý rừng

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1. Introduction

Forests are essential for the conservation of ecosystems and biodiversity. They play many important roles in supporting human life and environmental balance. Forests store large amounts of carbon in vegetation and soil, and they release oxygen into the atmosphere. This natural land cover helps regulate the surface temperature by providing shade and cooling through evaporation. Forests also protect river systems by reducing soil erosion. It is also evident that they reduce rainfall-induced landslides that can cause severe damage to settlements and infrastructure. According to Banskota et al. [1], forests help moderate climate change through carbon exchange. In addition, they strengthen water security by collecting and storing rainwater each year [2]. Their social and economic benefits show that natural forests are vital for both people and the environment.

Mapping deforestation is crucial for effective forest management. It helps reveal how forest areas change over time and identifies the main causes of forest loss. In some regions, deforestation occurs as a result of population growth, industrial expansion, logging, and agricultural development. Natural forests are often replaced by other types of land cover as infrastructure and the economy continue to grow. Mapping allows us to monitor the extent of these changes. Reliable deforestation detection provides vital information for planning forest conservation and restoration.

Traditional forest management often relies on extensive fieldwork and time-consuming reporting, especially for mountainous regions. To enhance the efficiency of this task, advanced analytical methods are increasingly being adopted. Remote sensing provides an effective way to observe and monitor forest changes [3]. Sentinel-2 imagery, with its 10-meter spatial resolution, offers valuable data for tracking deforestation at regional scales. Image processing and classification also play a central role; these new technologies enable the quick analysis and quantification of land cover changes over time.

Moreover, in recent years, deep learning has gained strong attention in this field due to its ability to automatically extract meaningful features from images, perform complex semantic segmentation, and handle nonlinear relationships in diverse environments [4]. Among deep learning techniques, convolutional neural networks (CNNs) have become one of the most widely used architectures [5]. CNNs can identify patterns at multiple levels of abstraction through convolutional filters and apply this knowledge to detect and map deforestation with high precision.

Accordingly, the main objective of this study is to examine the effectiveness of CNNs in detecting deforestation using Sentinel-2 true-color imagery in mountainous areas of Da Nang. Image patches with a size of 256×256 pixels were extracted from Sentinel-2 composites and classified into two categories: intact forest and deforestation. This approach aims to evaluate the potential of CNN-based models for forest change detection in complex terrain environments.

2. Research methodology and materials

2.1. Data collection

This study focuses on the mountainous regions of Da Nang as the research area. Forest management in these regions is challenging because the steep terrain makes many areas difficult to access, which limits fieldwork activities. To develop an effective deep learning model, proper data collection is essential. A total of 280 image samples were prepared, with 140 samples for each class: intact forest and deforestation. Among them, 200 samples were

used for training, 40 for validation, and 40 for testing to ensure a balanced dataset. The image samples in each subset were randomly selected within the study area to mitigate spatial autocorrelation. The Sentinel-2 imagery collected in 2025 served as the data source. To reduce the effect of cloud obstruction, images containing more than 5% cloud cover were filtered out. In this study, the image samples were retrieved from the Google Earth Engine platform. To enhance the dataset, data augmentation was applied to the training images through horizontal and vertical flipping, which increased sample diversity and improved model generalization. Figure 1 presents examples of the collected image dataset.

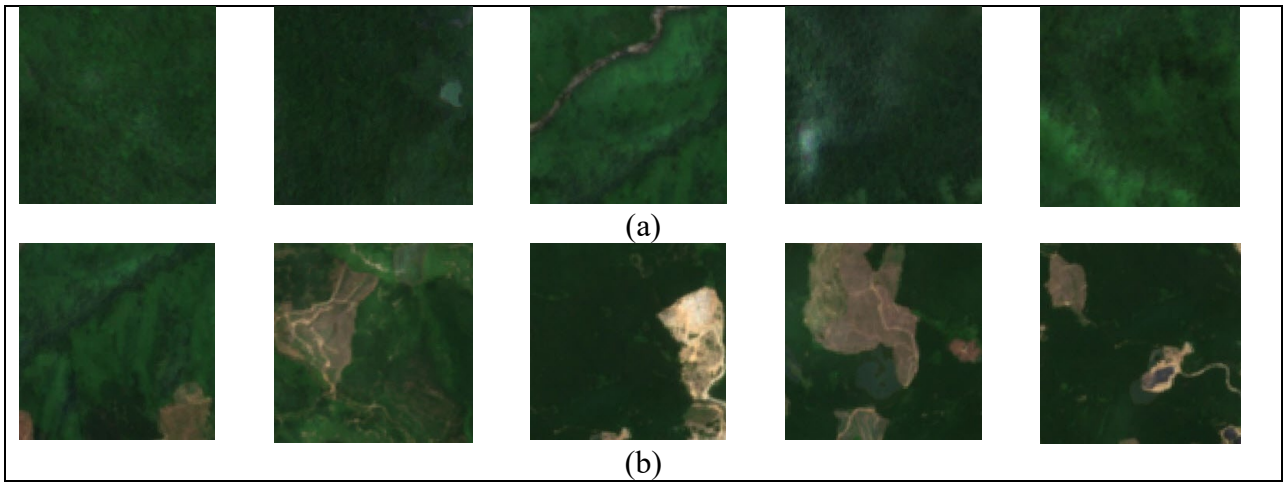


Figure 1. Illustration of the collected image dataset

2.2. Convolutional neural network (CNN)

Convolutional neural networks (CNNs) are a class of deep learning models that are designed specifically for image data, where pixels are arranged in a grid-like structure [6]. A CNN processes an image through stacked layers that automatically learn useful features, starting from simple patterns such as edges and textures and moving toward more complex structures [7]. This automatic feature extraction reduces the need for manual feature engineering and makes CNNs well suited for image classification tasks such as distinguishing intact forest from deforested areas in satellite imagery [5]. Their ability to capture local spatial relationships and maintain a hierarchy of features is especially important when analyzing remote sensing images, where deforestation patterns may appear in different shapes, scales, and positions. CNNs also handle high-dimensional data efficiently and can achieve high accuracy when supported by sufficient labeled samples. In this study, the CNN model is implemented using the PyTorch library (https://pytorch.org/), which provides flexible tools for building, training, and evaluating deep learning architectures on image datasets.

The convolutional neural network (CNN) used in this study is designed for the binary classification of image patches into intact forest and deforestation. Due to the limited size of the dataset, the input was restricted to three color channels—specifically the Red, Green, and Blue bands from Sentinel-2. The inclusion of other spectral channels was not considered, as high-dimensional inputs increase the risk of overfitting when training data is limited. Considering the input image size, the model consists of three convolutional blocks, each combining a convolution layer with 3×3 kernels, a ReLU activation function, and a max-pooling layer to gradually extract higher-level spatial features while reducing the spatial resolution of the input. After the feature extraction stage, the network uses a fully connected classifier that

flattens the feature maps, passes them through a linear layer with 128 hidden units and ReLU activation, and then applies a dropout rate of 0.5 before the final output layer with two neurons corresponding to the target classes.

The model is optimized with the Adam optimizer [8] using a learning rate of 1×10^{-4}, which provides stable and efficient convergence during training. The maximum number of training epochs and the batch size are selected to be 100 and 16, respectively. It is noted that overfitting is a key concern in this task, as the model may memorize the training data and perform poorly on unseen images if not properly controlled. To reduce this risk, the study uses a validation set and applies early stopping, where training is terminated once the validation performance no longer improves. This strategy helps the CNN model maintain better generalization to new image patterns.

3. Result and discussion

The training progress with the early stopping strategy is demonstrated in Figure 2. The training process shows stable convergence, with both training and validation losses decreasing steadily over epochs and remaining close to each other. This fact indicates good generalization of the trained model. The final results demonstrate strong performance, with classification accuracy rates of 0.94 on the training set and 0.93 on the test set. The F1 scores of 0.94 and 0.93 confirm that the CNN can reliably distinguish intact forest from deforestation patches. The recall of 1.00 on the test set further suggests that the model can effectively identify the deforestation samples, which is particularly important for forest monitoring applications. Classification outcomes yielded by the trained CNN model are illustrated in Figure 3.

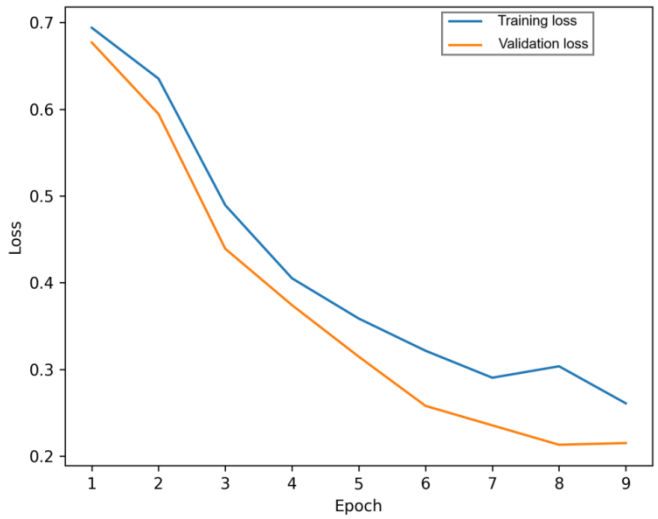


Figure 2. The training progress

Table 1. Classification performance

Phase	CAR	Precision	Recall	F1 score
train	0.94	0.90	0.99	0.94
test	0.93	0.87	1.00	0.93

As can be seen from the experimental results, the CNN architecture used in this study shows a clear advantage over traditional machine learning algorithms because they do not require manual feature extraction and can automatically learn discriminative patterns directly from raw Sentinel-2 image patches. This ability is particularly beneficial for complex forest landscapes, where spectral and textural characteristics of deforestation vary across space and are difficult to capture with hand-crafted features. Moreover, the training and testing classification accuracies are relatively similar,

which indicates that the model generalizes well to unseen data and does not suffer from notable overfitting. This balance between training and test performance supports the effectiveness of the regularization strategies used in the study. It also confirms the usefulness of the validation-based early stopping approach, which prevents the network from continuing to train after it stops improving on new data. To further analyze the spatial distribution of forest loss, *k*-means clustering was applied to the model's classification outputs to segment the image into forest and non-forest regions (refer to Figure 4). The *k*-means clustering is implemented via the scikit-learn library (https://scikit-learn.org/). The clustering process categorizes pixels with similar spectral properties into two clusters, and the proportion of pixels assigned to the non-forest cluster is then used to estimate the area affected by deforestation within the scene.

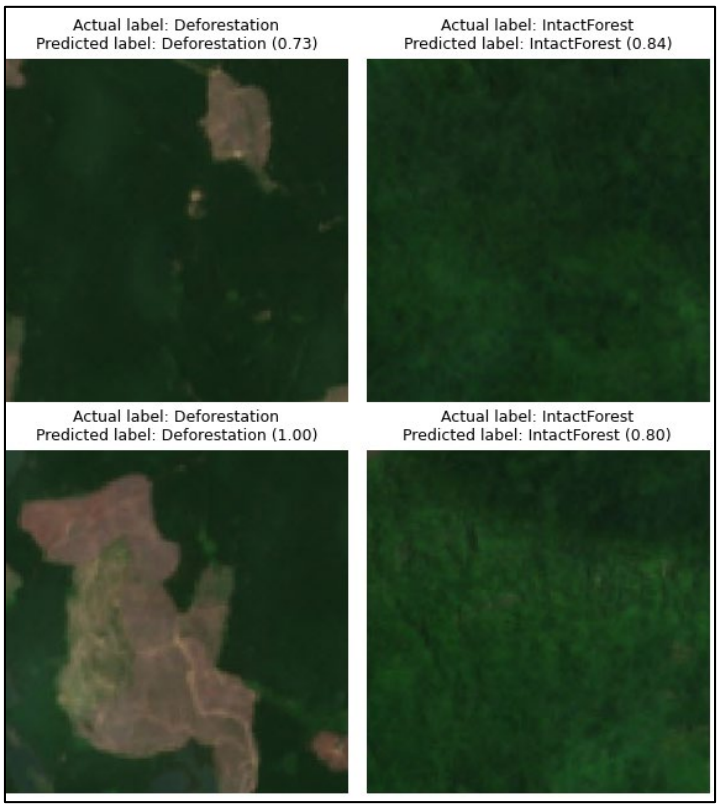


Figure 3. Demonstration of classification outcomes

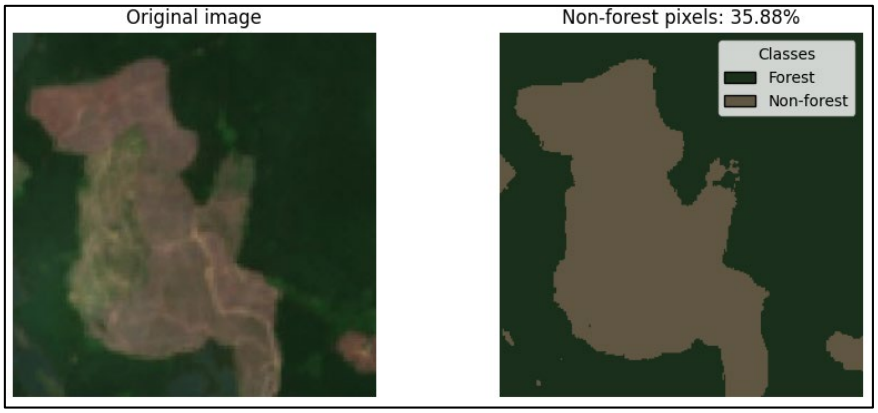


Figure 4. Result of image segmentation (using k-means clustering)

4. Concluding remarks

This study demonstrates that CNN model can effectively detect deforestation from Sentinel-2 true-color imagery in mountainous areas. The deep learning model achieved high accuracy and demonstrated robust generalization, despite being trained on a relatively small image dataset. The results confirm the suitability of the CNN-based model and show that combining classification with *k*-means-based image segmentation provides a practical way to estimate the proportion of non-forest pixels and quantify local forest loss.

However, the work is constrained by the small sample size, the use of only true-color bands, and the focus on a single year, which may limit the model's transferability to other periods of time, sensors, or forest types. Future studies could expand the dataset across multiple years and seasons, incorporate additional spectral bands or indices, and explore more advanced deep learning architectures such as ResNet, YOLO, attention mechanisms, or transformer-based models. Further work could also investigate semi-supervised learning to reduce labeling effort, integrate elevation and other geospatial data, and test the framework in a real-time processing setting.

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