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PERFORMANCE COMPARISON OF U-NET AND LINKNET WITH DIFFERENT ENCODERS FOR REFORESTATION DETECTION

Abstract. The **subject** of study is analysis of performance of artificial intelligence systems with different architectures for reforestation detection. **The goal** is to implement, train and evaluate system with different models for deforestation and reforestation detection. The **tasks** are to study problems and potential solutions in forestry for reforestation detection and present own solution. As part of model comparison, results are presented for different artificial neural network architectures with different encoders. For training and testing purpose custom dataset was created, which includes different areas of territory of Ukraine within different timestamps. Main research methods are literature analysis, experiment and case study. As a **result** of analysis of modern artificial intelligence methods, machine learning, deep learning and convolutional neural networks, high-precision algorithms U-Net and LinkNet were chosen for system implementation. **Conclusions.** The studied problem was stated formally and broken down in smaller steps; possible solutions were studied and proposed solution was described in details. Necessary mathematical background for analysis of the performance was provided. As part of the development, accurate deforestation/reforestation module was created. All analysis results were listed and a comparison of the studied algorithms was presented.

Keywords: reforestation detection; semantic segmentation; artificial neural network; machine learning; deep learning; convolutional neural network; U-Net, LinkNet.

Introduction

Forest recovery detection systems are crucially important for statistics collection, analysis and regulation of environment. This type of systems allow monitoring over different recovery strategies after logging, wildfires and floods overtime, which can lead to their improvement. Another important aspect of the monitoring is natural hazard prevention. Other benefits of systems may include water resource management, carbon level management and management of nature reserves. In the context of deforestation and overall forest analysis, numerous works have been written [1–3]. However, relatively few of them aim to create a reforestation detection system. The primary challenge in forestry lies in the vast areas of interests. Currently over 30% of the Earth's landmass consists of forest, which is equal to over four billion hectares of the territory [4]. In Ukraine, overall forest territory is 5,9% of whole territory or 10,4 million hectares (Fig. 1) [5].

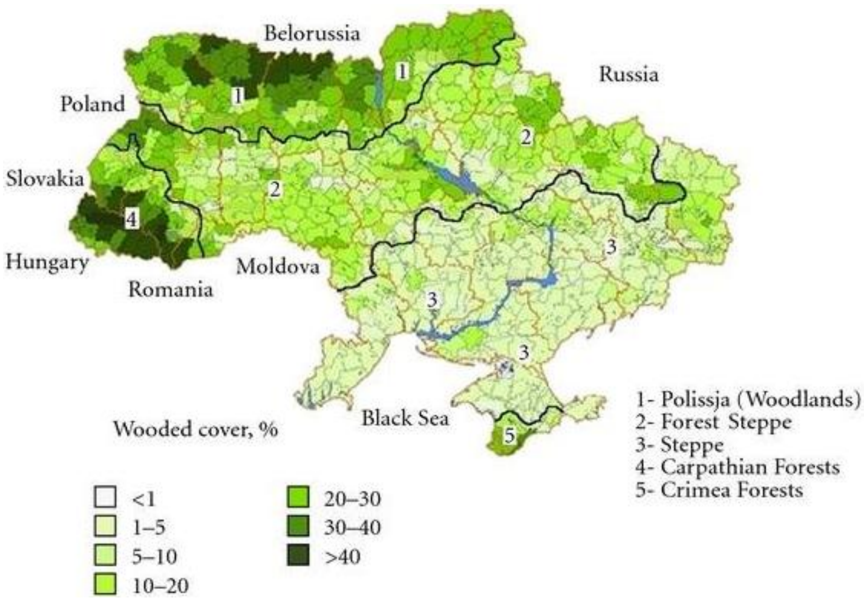

Fig. 1. Forestry of Ukraine

This statistics show, that it's impossible to maintain proper monitoring frequency of forests. Considering listed numbers, on-site analysis becomes simply impossible. Exactly for this purpose modern technologies, such as remote sensing and artificial intelligence, must be used.

Remote sensing is the technique for information collection about Earth's surface from airplanes or satellites. The method makes possible the obtaining of high quality multispectral images of the surface. However, images are often large, so these data must be pre-processed, before it can be used. For this purpose spectral indices are used.

With the help of spectral indices data for processing can be obtained, but actual processing unit consists of neural network model [6].

Problem statement

Mathematically speaking, reforestation detection is regression task – determine which territory was recovered. This type of analysis can be useful, but more complex approach must be considered. For example – generation of deforestation/reforestation map [7]. Normally this type of statistic can only be collected for two different timestamps, means, temporal analysis is performed. Output map can contain different types of change in surface cover. Following classes are considered: no data, deforestation, no change, reforestation, water bodies. First and last classes are important for data pre-processing from technical side of a question and for marking water bodies respectively. After five classes are defined, actual problem can be clearly classified – semantic segmentation. Semantic segmentation is one of most complex tasks in computer vision field [8, 9]. Semantic segmentation is process of mapping each pixel of input image to respective class on output image.

Dataset

As mentioned before custom dataset was created. For this purpose, remote sensing technology was used. There are two most popular solution within this topic– Landsat 8 [10] and Sentinel-2 [11]. Due to simplicity of data acquisition from Landsat 8, this satellite was used. It must be mentioned that the way both of these satellites work is very similar to each other, so the developed model can be easily adapted to Sentinel-2 imagery too [12].

Landsat 8 provides a multiple spectral images in the batch. The whole batch is about 1 Gb in size and can't be directly used for model training. That's why custom dataset is necessary. To generate the dataset some kind of data reduction algorithm is required. Spectral indices were chosen. Spectral index is mathematical calculation that use the reflectance values of different spectral bands. Spectral band is the simplest channel, which corresponds to one Landsat 8 batch image. Spectral band is reflection levels in specific range of wavelengths. At the end there are only two bands were used (Table 1).

Table 1 – **Used spectral bands and their characteristics**

Band index	Name	Wavelength range, mcm	Resolution, m
4	Red	0,64-0,67	30
5	NIR	0,85-0,88	30

Next, the area of interest must be selected. Images were acquired from EarthExplorer of United States Geological Survey [13]. The data were obtained from the territory of Donetsk region (Path: 175, Row: 27, 02.08.2015, 29.08.2019) and Dnipropetrovsk region (Path: 178, Row: 26, 06.07.2015, 03.07.2020). Two Landsat images from two different dates were chosen.

To determine changes of forest cover, general-purpose characteristics of vegetation is needed. This characteristic is Normalized Difference Vegetation Index (NDVI) [14, 15]. Only two of eleven bands are used to calculate this index:

$$NDVI = \frac{NIR - Red}{NIR + Red}, \qquad (1)$$

where NIR – near infrared reflection; Red – red reflection.

After images were selected, actual dataset can be created. To do this all bands are split on 64x64 pixel images. Total dataset contains over 32 thousand images, 16 thousand of which are train images, 13 thousand are test images and the rest 3 thousand was dedicated for validation.

Due to the fact, that the network must process two different images from two different points of time, the input of the model must have one more dimension, which equals to two. As mentioned earlier, there were defined five different classes of vegetation change. Finally, input and output images have dimensions 64x64x2 and 64x64x5 pixel respectively. Input images encoded as unsigned 8-bit integers (with values 0 – 255) and output images as unsigned 8-bit integers (with values 0 or 1). To plot deforestation map as image, each vectorized class must be converted to specific colour (Table 2, Fig. 2).

Table 2 – **Used spectral bands and their characteristics**

Class label	Class name	Colour components	Colour
0	no data	{0, 0, 0}	
1	deforestation	{255, 0, 0}	
2	no change	{255, 255, 0}	
3	reforestation	{0, 255, 0}	
4	water body	{0, 0, 255}	

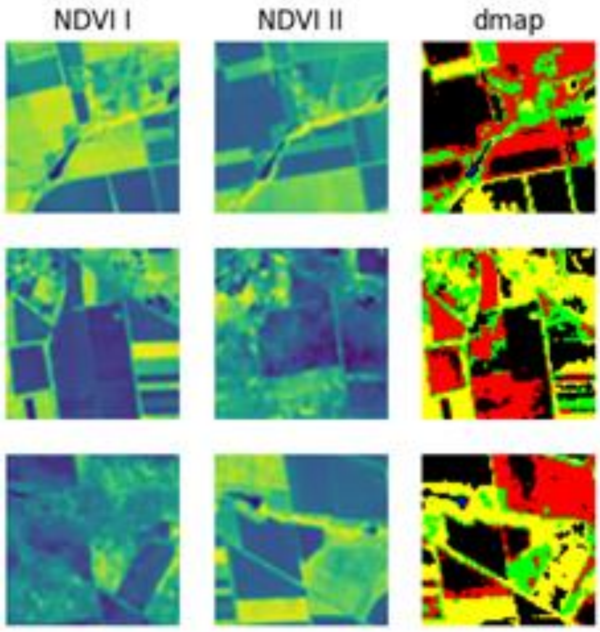

Fig. 2. Example of input and output images

Architectures

There are various approaches in the field of semantic segmentation nowadays [16–19], but nearly all of them follow the same architecture. Typically, it's involves encoder-decoder convolutional neural network, also known as an autoencoder neural network. A convolutional neural network (CNN) is subclass of artificial neural networks that imitates neural connections in human brain.

Convolutional neural network was built as an extension of regular neural network to allow the processing of more complex data, for instance, images [20]. In general, all CNNs follow a similar algorithm and their architectures are alike (Fig. 3).

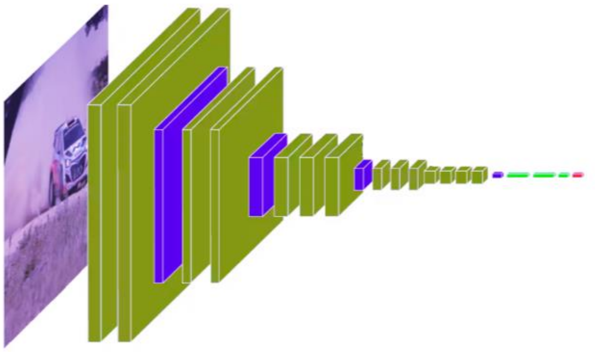

Fig. 3. General CNNs architecture

Purely mathematically, the convolutional can be defined as the integral of the product of the two functions after one if reflected about the y-axis and shifted [21]:

$$(f * g)(t) \coloneqq \int_{-\infty}^{\infty} f(\tau) g(t-\tau)\, d\tau, \qquad (2)$$

However, there is more intuitive way to understand convolution, especially on images – filtering. Everyone knows how to apply filters on images [22]. What's happening is for each part of an image (for example 3x3 pixel) some filter (also 3x3 pixel) is applied and after matrix multiplication some number is generated. This value represents an activation of the filter in this part of the image. After the same filter is applied to the whole picture, feature map is acquired. The shape of the feature map can be determined by the following formula:

$$n_{out} = floor\left(\frac{n_{in} + 2p - k}{s}\right) + 1, \qquad (3)$$

where n_{in}, n_{out} – input and output dimension respectively; k – filter size (in our case 3); p – padding size (in our case 1, so the size of feature map is equal to size of the input image); s – stride size (in our case 1).

An autoencoder network consists of two parts – an encoder and a decoder (Fig. 4) [23]. The encoder is simply CNN without a classification (fully connected layers) component. The decoder is "reversed" encoder. That means, it performs reversed convolution or up-convolution.

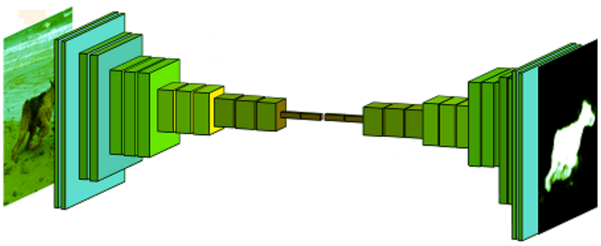

Fig. 4. Autoencoder architecture

Autoencoders are the most simple type of networks of the kind. The most popular variation of encoder-decoder networks is U-Net [24]. U-Net works and looks the same way as a regular autoencoder, but stacks skip connections between convolution and up-convolution blocks (Fig. 5).

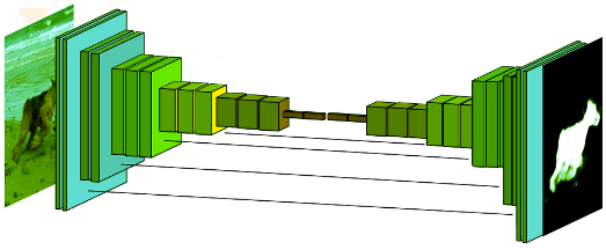

Fig. 5. U-Net and LinkNet architecture

Mathematically speaking, forward pass of U-Net can be described as series of applying convolution ($conv$), maxpooling ($MaxPool$) layers in encoder and transpose convolution ($TransConv$) with concatenation layers in decoder after each other:

$$conv_{ij}(X, k) = \sum_{m=0}^{M_1} \sum_{n=0}^{N_1} X_{(i+m)(j+n)} \cdot k_{nm}; \qquad (4)$$

$$MaxPool_{ij}(X) = \max\left(X_{ij} \ldots X_{(i+M_2)(j+N_2)}\right); \qquad (6)$$

$$TransConv_{ij}(X, k) =$$

$$= conv_{ij}(upsampling(X), k), \qquad (6)$$

where $i \in [0; width), j \in [0; height)$ – indices of output tensor; $width, height$ – weight and height of output image (or feature map); k – convolution kernel (or filter); X – input tensor; M_1, N_1 – sizes of convolution kernel (3x3 in our case); M_2, N_2 – sizes of maxpooling kernel; $upsmapling(X)$ – one of many up-sampling methods (zero padding in our case).

The second architecture of the network that was used is LinkNet [25]. LinkNet is very similar to U-Net, but instead of stacking one more layer, this networks sums them up. This way the network decoder part isn't getting bigger, in comparison to U-Net, but the information still passes through the network. Instead of concatenation of tensors, LinkNet adds them. This allows to reduce the size of decoder part of the network and that's why the time needed to "decode" the feature map into image is also reduced. Besides two general architectures, the encoder and the decoder can have different structures themselves. In the research, three different architectures were used: VGG16 [26], ResNet18 [27] and EfficientNetB0 [28]. VGG16 is the simplest encoder in the project. It consists of following cycling blocks: $conv$, $conv$, $MaxPool$. The network was chosen exactly because of its simplicity. ResNet18 is similar to VGG16 but has following pattern: $conv$, $conv$, $concat$, $MaxPool$. The concatenation operation is performed between the input of the block and two convolutions. The last but not least encoder architecture is EfficientNetB0 (Fig. 6). The most interesting network in the project. This network works exactly as ResNet, but instead of convolution blocks, Mobile Inverted Bottleneck (MBConv) blocks are used.

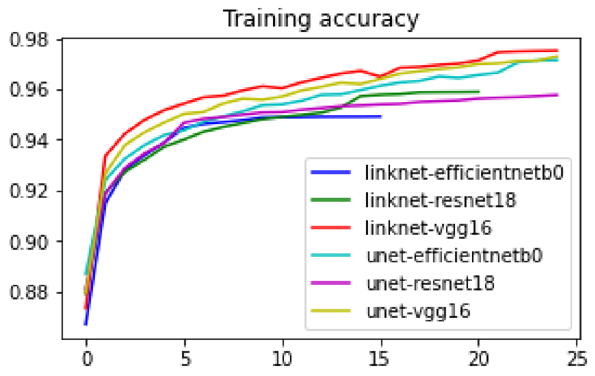

Fig. 6. Training accuracy of models

These block were originally presented in another architecture – MobileNetV2 [29]. These blocks can be generally described as follow:

$$MBConv(X, k_1, k_2, k_3) =$$
$$= concat(conv(DWconv(conv(X, k_1), k_2), k_3), X), \quad (7)$$

where k_1, k_3 – convolution kernels (or filters); k_2 – depthwise convolution kernel, almost same as regular convolution kernel, but with filter for each channel of the input tensor; X – input tensor; $concat$ – concatenation of two tensors; $DWconv$ – depthwise convolution. It works similarly to convolution, but applies separate kernel to each channel of the input tensor.

Model performance

Totally, more than 100 hours were spent training all described models with different encoder architectures (6 models in total) on GeForce GTX 1660Ti 6 Gb GPU. The accuracy metric was considered to be the most intuitively understandable and was chosen to base the comparison results on (Fig. 6):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \quad (8)$$

where TP – number of true positives cases; TN – true negatives cases; FP – false positives cases; FN – false negatives cases.

For more in-depth model's analysis following metrics were used (Table 3) [30]:

$$Precision = \frac{TP}{TP + FP}; \quad (9)$$

$$Recall = \frac{TP}{TP + FN}; \quad (10)$$

$$F1 = 2 \cdot \frac{Recall \cdot Precision}{Recall + Precision}. \quad (11)$$

Precision and recall show rates of type I and type II errors. That may come in handy for tasks, where one of two errors is considered more harmful. F1-Score is general metric, which considers the ration of type I and type II errors. Basically it's "balancing" metric between these errors.

In the end, the LinkNet model with VGG16 encoder was the best in terms of accuracy and overall F1-Score. The accuracy of this model is 97.45%.

The difference in performance of different encoders isn't much significant (Fig. 7).

Table 3 – **Final models evaluation**

Model	Accuracy, %	Precision	Recall	F1-Score
U-Net VGG16	97,36	0,94	0,95	0,95
U-Net ResNet18	96	0,92	0,92	0,92
U-Net EffNetB0	97,1	0,94	0,95	0,94
LinkNet VGG16	**97,45**	**0,95**	**0,95**	**0,95**
LinkNet ResNet18	95,35	0,92	0,92	0,92
LinkNet EffNetB0	94,6	0,9	0,85	0,88

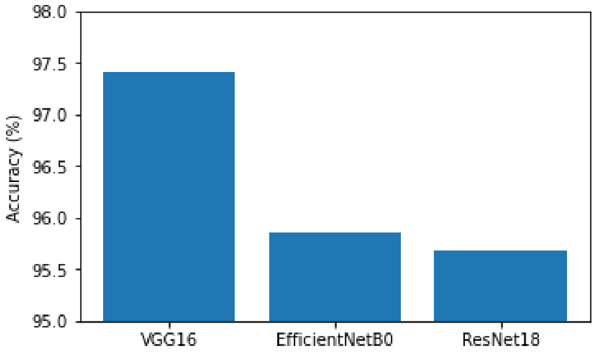

Fig. 7. The comparison of performance of encoders

The best encoder is the simplest one – VGG16. This model shows great results not only in final accuracy but also in speed of data processing.

In terms of general architecture, the decoder part of LinkNet models is smaller, because tensors are simply added to skip connections and not concatenated.

That's why training and processing speed of this architecture is higher.

From accuracy performance point of view, U-Net and LinkNet are equal. U-Net works just at 1.02% accuracy rate better, in comparison to LinkNet (Fig. 8).

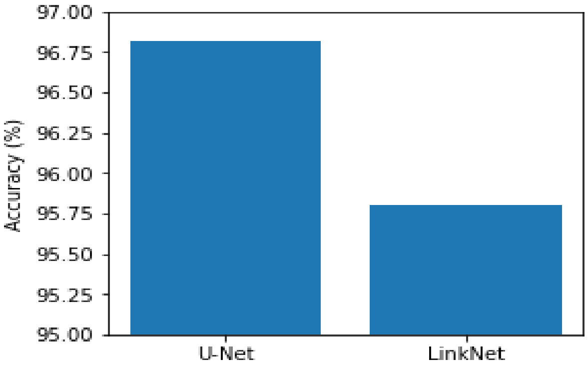

Fig. 8. The comparison of performance of U-Net and LinkNet

Conclusions

The aim of the work is to analyse the performance of U-Net and LinkNet architectures with different encoder parts for reforestation detection task. In the work, different aspects of the problem were described and the reforestation-deforestation task was stated formally. Different aspects of modern machine learning techniques were listed and described. The final solution was presented and deep learning models were trained, tested and compared to each other. As the result of applying different metrics, such as precision, recall, F1-Score and accuracy, the overview of performances was presented and explained.

As the result of analysis of the problem custom dataset of remote sensing imagery from Landsat 8/9 on the territory of Ukraine was created. Total dataset consist of 32768 images 64x64 pixels with two input channel for each image and total number of five classes for each output image. Next five classes were used: no data, deforestation, no change, reforestation (regrowth), water bodies.

Mathematical background was presented and explained. The way artificial neural networks and convolution neural networks work was described in-depth. Three different encoders: VGG16, ResNet18 and EfficientNetB0, were presented and their principles were described. Two autoencoder-like architectures: U-Net and LinkNet, were presented and the difference between them was presented.

As the result of the work, high precision models were trained. The best model of the project is LinkNet with VGG16 encoder. The accuracy of the model is over 97%. Despite the high accuracy of this model, the LinkNet model architecture generally works 1.02% (by accuracy) worse than U-Net. The comparison of encoders shows, that smaller VGG16 models perform better than EfficientNetB0 or ResNet18.

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Порівняльна характеристика U-Net та LinkNet з різними шифраторами для визначення відновлення рослинності

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Анотація. Предметом дослідження є аналіз продуктивності штучних інтелектуальних систем з різною архітектурою для визначення відновлення рослинності. **Метою дослідження** є реалізація, навчання та перевірка працездатності системи з різними моделями для визначення знищення та відновлення рослинного покрову. **Завданнями роботи** є вивчення можливих шляхів вирішення задачі визначення відновлення зеленого покрову, а також представити власне рішення. Як частина порівняння моделей, представленні результати семантичної сегментації поверхні для різноманітних штучних нейронних мереж із різною архітектурою та з різними шифраторами. Для навчання та тестування було розроблено власний набір даних, котрий включає різні ділянки території України, котрі були отримані за різні дати. Основними методами дослідження є аналіз літератури, експеримент та тематичні дослідження. Під час аналізу різних сучасних методів штучного інтелекту, машинного навчання, глибокого навчання та згорткових нейронних мереж були обрані високоточні алгоритми U-Net та LinkNet для реалізації системи. **Висновки**. Досліджена проблема була формально визначена та розбита на менші кроки: можливі шляхи вирішення проблеми були дослідженні, а також представлення рішення було описано в деталях. Було висвітлено необхідні математичні аспекти для аналізу працездатності. Під час розробки було створено точний модуль для визначення знищення/відновлення рослинності. Було надано усі результати досліджень та порівняльна характеристика досліджених алгоритмів.

Ключові слова: визначення відновлення рослинності; семантична сегментація; штучна нейронна мережа; машинне навчання; глибоке навчання; згорткові нейронні мережі; U-Net; LinkNet.