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BATHYMETRIC AND HYDROGRAPHIC PARAMETERS OF WATER BODIES OVER NEURAL NETWORKS

НЕЙРОНДЫҚ ЖЕЛІЛЕР АРҚЫЛЫ СУ ОБЪЕКТІЛЕРІНІҢ БАТИМЕТРИЯЛЫҚ ЖӘНЕ ГИДРОГРАФИЯЛЫҚ ПАРАМЕТРЛЕРІН АНЫҚТАУ

ОПРЕДЕЛЕНИЕ БАТИМЕТРИЧЕСКИХ И ГИДРОГРАФИЧЕСКИХ ПАРАМЕТРОВ ВОДНЫХ ОБЪЕКТОВ ЧЕРЕЗ НЕЙРОННЫЕ СЕТИ

Abstract. *Today, there is an increased use of artificial intelligence systems to solve the latest mixed science and technology problems. And Earth remote sensing (ERS) is one of these problems.*

As it applies to ERS problems, neural network approaches can be conventionally classified as algorithms indirectly using physical and non-physical quantities, i.e. measure values from satellite tools. In other terms, a function linking input quantity and output (such as the probability of a particular class in a classification problem) is approximated by the algorithms specified, unlike other approaches where this function is usually explicitly asserted. The widespread use of classification algorithms is the case of an explicit physical approach based on spectral analysis and threshold methods when physical quantities (e.g., spectral brightness ratio, luminous temperature, etc.) or spectral indices are evaluated by means of thresholds specified for each class. This approach requires complex dependencies to get more exact results in an unknown analytical form. However, using neural networks such difficulties can be overcome [1].

The article is aimed to highlight the primary results to practice the neural network in bathymetric and hydrographic parameters of water bodies identification.

Keywords: *Neural network, water body, satellite imagery, bathymetric and hydrographic parameters.*

Аңдатпа. *Бүгінгі таңда түрлі сипаттағы өзекті, ғылыми-техникалық мәселелерді шешу үшін жасанды интеллект жүйелерін белсенді қолдану процесінің кеңінен пайдаланылуы байқалады. Мұндай міндеттерге Жерді қашықтықтан зондтау аймағы (ЖҚЗ) кіреді.*

ЖҚЗ міндеттеріне қатысты нейрондық желілерді қолдануға негізделген тәсілдерді физикалық және физикалық емес шамаларды, яғни спутниктік аспаптарды өлшеу деректерін жасырын пайдаланатын алгоритмдер ретінде шартты түрде жіктеуге болады. Басқаша айтқанда, кіріс шамалары мен шығыс нәтижесін байланыстыратын функция (мысалы, жіктеу тапсырмасындағы белгілі бір сыныптың ықтималдығы), бұл функция әдетте нақты түрде берілген басқа тәсілдерден айырмашылығы, көрсетілген алгоритмдермен жуықталады. Нақты физикалық тәсілдің мысалы ретінде физикалық шамалар (мысалы, спектрлік жарықтық қатынасы, жарықтық температурасы және т.б.) немесе спектрлік индекстер әр класс үшін берілген шектермен бағаланатын спектрлік талдау мен шекті әдістерге негізделген жіктеу алгоритмдерін *кеңінен қолдану үлгісін қарастыруға болады. Бұл тәсіл белгісіз аналитикалық формада дәлірек нәтиже алу үшін күрделі тәуелділіктерді ескеруді талап етеді. Алайда, нейрондық желілерді қолдану арқылы мұндай қиындықтарды жеңуге болады [1].*

Мақаланың мақсаты – су объектілерінің батиметриялық және гидрографиялық параметрлерін анықтауда нейрондық желіні қолданудың алғашқы нәтижелерін жариялау.

Түйін сөздер: *нейрондық желі, су объектісі, спутниктік сурет, батиметриялық және гидрографиялық параметрлер.*

Аннотация. *В настоящее время наблюдается рост активного использования систем искусственного интеллекта для решения актуальных, научно-технических задач различного характера. В число подобных задач входит область дистанционного зондирования Земли (ДЗЗ).*

Применительно к задачам ДЗЗ подходы на основе применения нейронных сетей можно условно классифицировать как алгоритмы, неявно использующие физические и нефизические величины, т.е. данные измерений спутниковых приборов. Другими словами, функция, связывающая входные величины и выходной результат (например, вероятность определенного класса в задаче классификации), аппроксимируется указанными алгоритмами, в отличие от остальных подходов, в которых эта функция обычно задается явным образом. Примером явного физического подхода является широкое использование алгоритмов классификации, основанных на спектральном анализе и пороговых методах, когда физические величины (например, спектральное отношение яркости, яркостная температура и др.) или спектральные индексы оцениваются с помощью пороговых значений, заданных для каждого класса [1]. Такой подход требует учета сложных зависимостей для получения более точных результатов при неизвестной аналитической форме. Однако с использованием нейронных сетей подобные сложности могут быть преодолены.

Целью статьи является освещение первостепенных результатов применения нейронной сети в определении батиметрических и гидрографических параметров водных объектов.

Ключевые слова: *нейронная сеть; водный объект; спутниковое изображение; батиметрические и гидрографические параметры.*

Introduction. Data technologies from spacecraft make progress still in their development. Such data provide a range of information on the Earth's surface, macro- and microphysical parameters of cloud formations and atmospheric conditions. They allow to solve a lot of fundamental and applied scientific problems related to integrated monitoring of climate and ecosystems, meteorological phenomena prediction, etc., in an operational mode with a rather high degree of accuracy. The alternative is self-learning algorithms modeling dependencies based on the learning data itself. The advent of high-performance computing systems and customized software libraries has led to an increased use of machine learning technology and in-depth problem-solving learning, including this area of expertise [1].

Research and development on bathymetric water data and water level prediction are important for safety and disaster prevention. Several research groups presented innovative approaches to solving this problem, using in-depth learning and high-performance computing mechanisms.

The J. Gandhi team has developed a deep learning model based on Convolutional Neural Network (CNN), which classifies flood water depth into different categories based on user or passenger imagery. This approach makes the system more user-friendly. Moreover, they have integrated this model with a cross-platform application, allowing passengers to easily provide data on water levels. The system is also equipped with an alert function, which informs other users of places where water levels exceed thresholds. This further increases the safety and importance of the solution [2].

Mahmoud Al Najar and his team investigated the use of neural networks to assess bathymetric parameters of water bodies based on multispectral images. The designers developed a neural network architecture capable to get deep information from satellite data and trained it on tagged datasets. The results showed high accuracy and prospects of this approach for bathymetry [3].

Di Wu's team has offered a high-performance CNN processor that is based on FPGA (fieldprogrammed gate array) to improve data processing efficiency. They developed two specialized computing mechanisms, the Conv Engine and Dwcv Engine, designed in turn for point and depth reduction. These computing mechanisms are optimized to perform CNN operations and provide high performance, allowing fast and accurate analysis of images and water depth data [4].

The authors of Buongiorno Nardelli, B. A Deep Learning Network to Retrieve Ocean Hydrographic Profiles from Combined Satellite and In Situ Measurements present an innovative method of deep learning which, after learning based on rare combined vertical profiles on site, converts sea surface satellite data into depth information. This approach is based on a multi-level neural network that includes long-term and short-term memory, as well as the Monte Carlo elimination method. The methodology is used to analyse data collected between 2010 and 2018 in the North Atlantic [5].

A Background Paper shows that the application of neural networks in hydrography and bathymetry assessment is an area that is growing rapidly and significantly improves the accuracy and efficiency of water body analysis processes. Machine learning contributes to the automation and improvement of hydrographic parameter estimates, which are important in geographic information systems, environmental monitoring and other water-related applications [6].

This article shows the development results and the use of algorithms with neural networks to solve problems in hydrometeorology related to the classification of multispectral satellite imageries.

Research Materials and Methods. In order to identify the bathymetric and hydrographic parameters of water bodies, it was decided to apply the capabilities of neural networks, as in the segmentation of satellite imageries.

The algorithm for the construction of bottom maps and the identification of water body depths begins with the loading of satellite imagery into the neural network. Then the output is a bit mask, where the value is 0, meaning that there is no water on this pixel, and the value is 1, that the water object is found. The mask processes the image for small water objects, clipping them off from the image, leaving the largest one.

The neural network architecture chosen for this research is U-Net, which is a specialized architecture for solving problems of semantic image segmentation. The U-Net choice is based on its outstanding efficiency in this context, ease of use and small computer resource requirements. Moreover, U-Net delivers better segmentation objectives than alternative architectures such as FastFCN, Gated-SCNN, DeepLab, and Mask R-CNN.

U-Net is rated as one of the standard Convolutional Neural Network (CNN) architectures for image segmentation objectives, which require both the identification of object classes in the image as a whole and the image segmentation into separate areas called segments to create masks that divide different classes. U-Net architecture is characterized by two main components: contracting path (encoder) and symmetric expanding path (decoder) [7].

The contracting path is designed for a wide image context and extracts high-level features. This is achieved by serial attached application of convolution layers, sub-sampling operations (e.g., maximum consolidation operations) and activation functions. As a result of this procedure, the model creates a more abstract representation of the image [8].

The expanding path, on the other hand, is designed for precise localization of objects and creation of segmentation masks. It includes transposed or interpolation operations to increase data dimension, followed by sequential convolutional layers that integrate information from the contracting path and allow models to precisely identify the object boundaries in the image [9].

As a result, the U-Net architecture can effectively solve image segmentation problems and is widely used in areas where it is important to accurately localize and highlight objects in images, such as medical diagnostics, geographic information systems and other areas [10].

Figure 1 shows the architecture of the neural network including two main parts: the contracting path (left) and the expanding path (right). Contracting path is the standard architecture of a convoluted neural network. This path begins with the sequential application of two 3×3 convolution operations. The ReLU activation function is then applied after each convolution, which helps to introduce non-linearity into the model. This is followed by a maximum amalgamation operation (2×2 of degree 2), which reduces spatial resolution of the data [11].

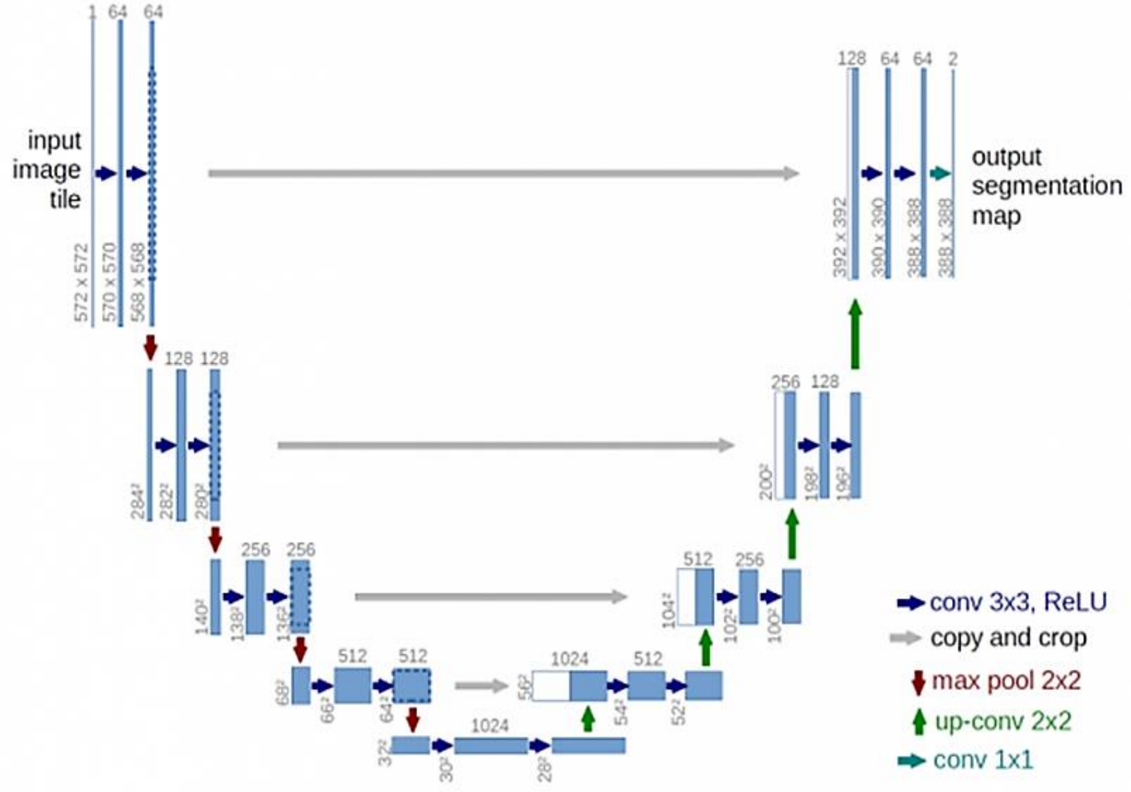

Figure 1. U-net architecture (example of 32×32 pixel image-lowest) [8]

The contracting path makes an important function of extracting high-level features from the input data and reducing them to a lower dimension. This allows the network to highlight abstract hierarchical features that are commonly required for segmentation and classification objectives.

This is followed by an expanding path that begins with a transposed or interpolation operation increasing data dimension. Then the convolution operations are applied again to combine information with a contracting path. This process is ongoing until final segmented data are available [12].

The network architecture including a contracting and expanding path, allows the neural network to efficiently extract information from the input data and produce precise segmentation of objects in the images. This architecture is the standard choice for semantic segmentation objectives and provides high performance in such applications [13].

Results and discussions. The neural network shown in this context is developed in the Python programming language using the PyTorch framework. This framework is a convenient tool for creating and learning deep neural networks and is widely used in artificial intelligence and machine learning [14].

The program code below shows an operation of this neural network:

```
import numpy as np
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
import torchvision
import torchvision.transforms as transforms
import os
import glob
import cv2
from PIL import Image
from albumentations import HorizontalFlip, VerticalFlip, Rotate
import torch.nn.functional as F
import matplotlib.image as mpimg

size = (256, 256)

import torch

torch.cuda.is_available()
# %%
from torch import nn
import segmentation_models_pytorch as smp
from segmentation_models_pytorch.losses import DiceLoss
import cv2

device = ‘cpu’

EPOCHS = 45
BATCH_SIZE = 32
LR = 0.001

ratio = 0.5  # Various ratios could perform better for visualization
sample_num = 18

ENCODER = ‘resnet50’
WEIGHTS = ‘imagenet’

# Creating a model
class SegmentationModel(nn.Module):
    def __init__(self):
        super(SegmentationModel, self).__init__()

        self.arc = smp.Unet(
            encoder_name=ENCODER,
            encoder_weights=WEIGHTS,
            in_channels=3,
```

```
            classes=1,
            activation=None
        )

    def forward(self, images, masks=None):
        logits = self.arc(images)
        if masks != None:
            loss1 = DiceLoss(mode=’binary’)(logits, masks)
            loss2 = nn.BCEWithLogitsLoss()(logits, masks)
            return logits, loss1, loss2
        return logits

# %%
def read_img(path):
    im = Image.open(path)
    img = im.resize((256, 256))
    img = np.array(img)
    img = np.transpose(img, (2, 0, 1))
    img = img / 255.0
    img = torch.tensor(img)
    return img

# %%
model = SegmentationModel()
model.to(device)
# %%

# The lake is being separated from the snapshot
probability = 0.3
model.load_state_dict(torch.load(‘./best_model.pt’, map_location=torch.device(‘cpu’)))
path = input("Snapshot path:")
image = read_img(f”{path}”)
logits_mask = model(image.to(device, dtype=torch.float32).unsqueeze(0))
pred_mask = torch.sigmoid(logits_mask)
pred_mask = (pred_mask > probability) * 1.0
# %%
#
# plt.imshow(np.transpose(pred_mask.detach().cpu().squeeze(0), (1, 2, 0)))
new_img = np.transpose(pred_mask.detach().cpu().squeeze(0), (1, 2, 0))
new_img = np.array(new_img)
new_img *= 255
new_img = np.concatenate([new_img, new_img, new_img], axis=-1)
cv2.imwrite(“mask.jpg”, new_img)
# %%
import numpy as np
import cv2 as cv

im = cv.imread(‘mask.jpg’)
```

```
assert im is not None, “file could not be read, check with os.path.exists()”
imgray = cv.cvtColor(im, cv.COLOR_BGR2GRAY)
ret, thresh = cv.threshold(imgray, 127, 255, 0)
contours, hierarchy = cv.findContours(thresh, cv.RETR_TREE, cv.CHAIN_APPROX_SIMPLE)
c = max(contours, key=cv2.contourArea)
img = np.zeros((256, 256, 3), np.uint8)
# cv.drawContours(im, c, -1, (0, 255, 0), 2)
final = cv2.fillPoly(img, pts=[c], color=(255, 255, 255))
cv.imwrite(“mask.jpg”, final)
# %%
mask = cv.imread(‘mask.jpg’)
img_old = Image.open(‘1111.jpg’).resize((256, 256))
img_old = np.array(img_old)
cutted = cv2.bitwise_and(img_old, mask)
plt.imsave(‘cutted_lake.jpg’, cutted)
print
 " probability in line 80 in the range from 0 to 1")
```

A bit mask used allows the separation of water and dry surfaces in satellite imageries, which is an important step in the pre-processing of data for the further operation of the neural network. A neural network learnt on data-based can then automatically identify the largest water body in the image, which can be useful for various applications, including hydrography and water monitoring [15].

Figure 2. Initial satellite imagery of a water body

Figure 3 shows the processing of the satellite imagery depend on the initial objectives of the neural network. Bit operations require images to be black and white.

The activation layer of this neural network includes two mathematical functions: Rectified Linear Unit (ReLU) and sigmoid function. The ReLU function is designated by the following formula: $f(x) = \max(0, x)$ which allows the activation of neurons only at positive input values. Sigmoid function is designated as $s(x) = 1 / (1 + e^{(-x)})$ and provides output values in [0, 1] interval, which is qualified for binary segmentation. Neural network was learnt on 50 epochs with learning_rate=1e-3, batch_size=32 and data augmentation.

Final accuracy: 97.8%.

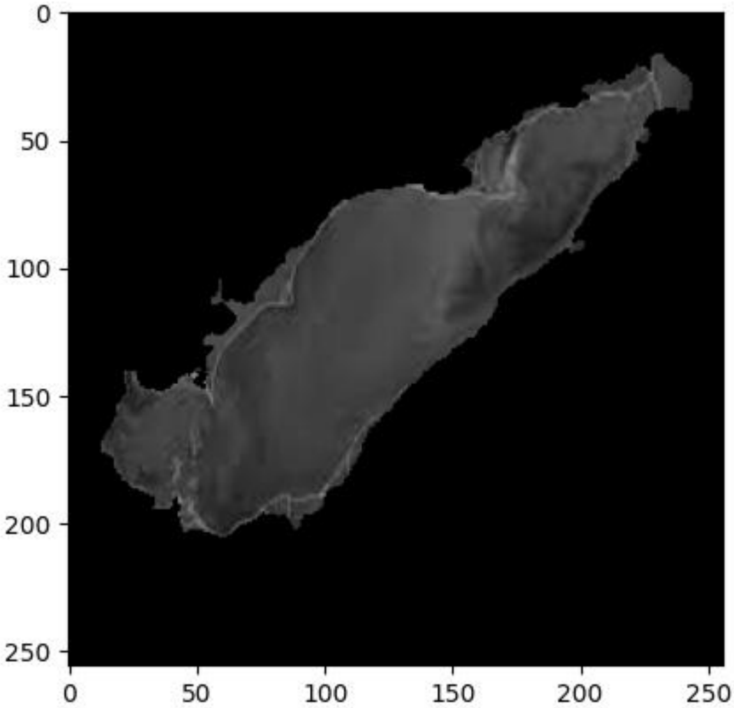

Figure 3. The result of the bit mask is the identification of the boundaries of a water body and its separation in the image

Conclusion. Neural network learning was performed on an extensive dataset containing about 2,800 images and associated bit masks. Link to collected satellite imagery: https://cloud.mail.ru/public/G97u/VjmQ4GH4C. The learning process continued for 50 epochs with the parameters learning_rate=1e-3 and batch_size=32, and data augmentation was applied to it, contributing to the model's ability to generalize.

The final accuracy of the neural network reached an impressive level of 97.8%, which indicates a high quality characteristic of the developed model. It is important to emphasize that machine learning models have the advantage of being able to account for more dependent variables than classical physical models, which finally results in greater accuracy [16].

The effective use of neural networks in the processing of satellite imagery data is proved by our research. The classification of objects based on textures and image features has a wide range of practical applications, including the creation of bathymetric maps of the water bodies bottom.

It is important to emphasize that further learning of the neural network is underway. At the end of this phase it will be possible to identify the depth of water bodies and to generate bathymetric maps, which will further improve the research methodology and expand its scope of application in hydrography and other related areas of science and technology.

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