Neural network analysis of hyperspectral images of soil

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***Abstract* — The article approaches to the classification of high-resolution hyperspectral images in the problem of classification of soil species is proposed. A spectral-spatial convolutional neural network with compensation for lighting variations is used as a classifier. The effectiveness of the proposed approach in the problem of classification of hyperspectral images of soils obtained by a scanning hyperspectral camera is shown. The essence of the developed method is to use binary classification together with multiclass, thereby improving the result of the latter.**

Keywords* — *Hyperspectral images, convolutional neural networks, spectral-spatial classification of hyperspectral images.

I. Introduction

The global agriculture sector is facing growing challenges caused by a number of factors. Farmers are looking for ways to increase the yield and efficiency of their production, using point farming.

Hyperspectral images can be used to solve tasks such as monitoring the physiological state of vegetation and soil: assessment of the level of nitrogen nutrition of plants [1], determination of soil and plant moisture during the growing season [2], assessment of the accuracy of recognition of soil and plant objects [3], chlorophyll content [4], early symptoms of diseases and much more. Precision agriculture uses irrigation, fertilizers or pesticides more purposefully, and also reduces time and material costs [5].

II. Hyperspectral data

The survey of soil samples (fig. 1) was carried out using a small-mass–sized slit scanning hyperspectral camera based on the Offner scheme (hereinafter referred to as a hyperspectrometer), designed to conduct hyperspectral surveys in the visible optical range of 400-1000nm (at least 250 channels) of objects of the underlying surface for further data processing and classification based on spatial-spectral features.

Fig. 1. 240 hypercube layer – 956 nm

III. Neural network classification

Two approaches based on the modified spectral-spatial convolutional neural network [6] were chosen for soil classification. This network has proven itself well in the agriculture tasks [7, 8].

The first approach can be described as “classic". It used simple multiclassing using the spectral-spatial network [6], cross-entropy was used as a loss function. Precision, recall, f1-score (for each class and average for all classes) were considered as classification quality assessment metrics.

The second approach uses the results of multiclass classification, but it also adds certain number (n) of binary results for individual classes. At the training stage, in addition to the “classical” multiclassing on the full volume of data, the dataset is divided into certain (N) binary sets, where each class of the initial markup acts as the target class. Then, ensemble of networks trains for each binary set. After receiving the results of the binary classification, the model evaluates the class classification by the f1-score, precision and recall metrics, and then compares the results of the binary model for an individual class and the results for the corresponding class in the multiclass model. Then the process of setting up the future “collector” of the final result begins. All results of binary models are sorted from the worst model (f1-score acts as a metric) to the best. The best models compare their results with the corresponding classification results of the multiclass model.

IV. Results

Color reconstructed image from HSI of soils in Fig.2 is shown.

Fig. 2. RGB from hyperspectral data image.

Laboratory chemical analysis of soils was carried out. For the experiment, the data were placed on the carbon content with the results of chemical analysis.

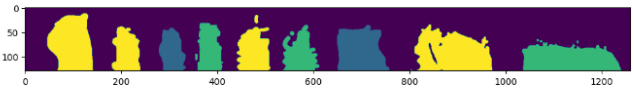

Fig. 3. Marking by the carbon content in the soil.

In the markup in Fig. 3:

- blue color - low substance content;
- green color - average substance content;
- yellow color - high substance content.

After training the neural network, the predictions of the "classical" approach are shown on Fig. 4 and Table I.

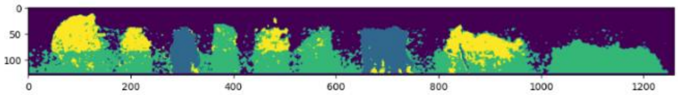

Fig. 4. Results of the classical approach of carbon classification.

TABLE I. METRICS OF THE MULTICLASS CARBON CLASSIFICATION APPROACH.

	precision	*recall*	*f-1*
1	0.97	0.80	0.87
2	0.85	0.89	0.87
3	0.35	0.93	0.51
4	0.84	0.50	0.63
weighted avg	0.87	0.77	0.79

Relying on prediction images and metrics with ensemble is shown on Fig. 5 and Table II.

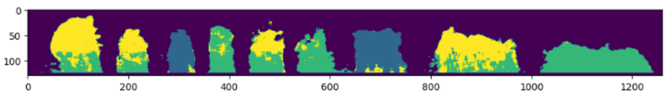

Fig. 5. Results of the ensemble spectral-spatial networks carbon classification approach.

TABLE II. METRICS OF THE ENSEMBLE OF SPECTRAL-SPATIAL NETWROKS APPROACH TO CARBON CLASSIFICATION.

	precision	*recall*	*f-1*
1	0.95	0.93	0.94
2	0.91	0.87	0.89
3	0.55	0.87	0.68
4	0.84	0.62	0.71
weighted avg	0.89	0.87	0.87

Based on the numerical representation of the classification results, we can conclude that the multibinary approach increases the average accuracy to 10% by the average value on the data presented in the work.

V. Conclusion

As a result, hyperspectral images of soils with data on their mineral composition were obtained, and a classification method with ensemble of networks was developed.

The ensemble of spectral-spatial networks approach is compared with the "classical" multiclass classification: the ensemble of networks is more accurate compared to the classical network for multiclass classfication.

References

[1] Surin, V. G. Possibilities of using the Lepton hyperospectrometer for monitoring the state of the soil-plant complex / V. G. Surin, K. G. Moiseev, A. E. Kurashvili // Agrophysics. – 2012. – №4(8). – P. 34 – 45.

[2] Shchedrin, V. N. Ground-based hyperspectral equipment for measuring vegetative indices in precision irrigation of agricultural crops / V. N. Shchedrin, S. M. Vasiliev, A. N. Babichev, R. V. Skidanov, V. V. Podlipnov, Yu. N. Zhuravel // Scientific Journal of the Russian Research Institute of Land Reclamation Problems. – 2018. – №1(29). – P. 1 – 14.

[3] Balter, B. M. Evaluation of the accuracy of recognition of soil and plant objects according to hyperspectral sensing and the quickbird satellite scanner/ B. M. Balter, D. V. Vorontsov, V. V. Egorov, A. A. Ilyin, A. P. Kalinina, A. G. Orlov, I. D. Rodionov, I. P. Rodionovo // Modern problems of remote sensing of the Earth from space. – 2008. – P. 40 – 48.

[4] Ignatova, M. A. Seasonal dynamics of NDVI in maple species / M. A. Ignatova, B. L. Kozlovsky, P. A. Dmitriev, O. I. Fedorinova, A. A. Dmitrieva, T. V. Varduni // Scientific electronic periodical of the SFU "Living and biocontainable systems". – 2022. – №39

[5] Meshchaninova, E. G. Application of Earth remote sensing data in agriculture / E. G. Meshchaninova, Yu. A. Stepkina // Economics and ecology of territorial entities. – 2020. – T.4, № 4. – P.72-77.

[6] He, M. Multi-scale 3D deep convolutional neural network for hyperspectral image classification / M. He, B. Li, H. Chen // IEEE Int Conf on Image Processing (ICIP). – 2017. – P. 39043908.

[7] Makarov, A.R. Neural network classification of coffee varieties on hyperspectral images / A. R. Makarov, V. V. Podlipnov, N. A. Ivliev, A. V. Nikonorov, D. I. Ulyanov, N. A. Firsov // VIII International Conference on Information Technology and Nanotechnology (ITNT). – 2022. –P. 1-3. doi: 10.1109/ITNT55410.2022.9848735.

[8] Firsov, N.A. Neural network-aided classification of hyperspectral vegetation images with a training sample generated using an adaptive vegetation index / N.A. Firsov, V.V Podlipnov, N.A. Ivliev, P.P. Nikolaev, S.V. Mashkov, P.A. Ishkin, R.V. Skidanov, A.V. Nikonorov // Computer Optics. – 2021. – Vol.45(6). – P. 887-896. DOI: 10.18287/2412-6179-C0-1038.