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PERFORMANCE COMPARISON OF CNNS ON HIGH-RESOLUTION MULTISPECTRAL DATASET APPLIED TO LAND COVER CLASSIFICATION PROBLEM

Multispectral images acquired by satellites have been used in many fields such as agriculture, urban change detection, finding fire-hazardous forest areas, and real-time surface monitoring. The central issue in remote sensing analysis is land use and land cover classification. Land use and land cover classification (LULC) is the process of classification into meaningful classes based on the spectral characteristics of remote sensing data. Land use and land cover classification is a challenging task due to the complex nature of the Earth's surface. The accuracy of solving the issue using deep learning approaches depends on the quality of the remote sensing data, the choice of the classification algorithm. The ability to obtain high-resolution multispectral images periodically could dramatically improve remote sensing solutions. In this study, we propose a solution for the land cover and land classification problem of high-resolution remote sensing data by applying deep learning methods using EuroPlanet geo-referenced high-quality images with four bands and pixel resolution of 204x204 per image, and acquired by Planet platform in 2020-2022 years. The dataset consists of 25911 images with spatial resolution up to 3.125 meters per pixel and 10 different classes. In the past decade, artificial neural networks have shown great performance in solving complex image classification tasks. For the dataset evaluation, we have taken advantage of state-of-art pretrained convolutional neural network models ResNet50v2, EfficientNetV2, Xception, VGG-16, and DenseNet201 with fine tuning. It has been established that DenseNet201 pretrained neural network outperformed other models. The accuracy of the test data was 92.01 % and the F1 metric was 91.63 %. In addition, bands evaluation for the dataset was carried out. Overall classification accuracy of 93.83 % and F1 score of 93.56 % were achieved by DenseNet201 model. The results could be used for area verification, real-time monitoring, and surface change detection. Nowadays, this is very helpful for Ukrainian territory because of the Russian invasion and the country's recovery in the future.

Keywords: *EuroPlanet; pretrained convolutional neural network; multispectral images; spectral indexes; land cover; remote sensing.*

1. Introduction

1.1 Motivation for research

Nowadays, remote sensing plays a vital role in wide range of Earth observation issues. The technique is used for acquiring information from remote sensors (such as satellites) and provides practical techniques for monitoring and change detection of physical parameters of objects. In recent years, the availability of remote sensing data has periodically opened opportunities to solve the issues in various fields of study. Land use and land cover classification (LULC) helps in observing and detecting changes in ecosystems over time. Obtaining information is essential for understanding the impact of natural disasters and human activities on the environment. LULC contributes to climate change study and environment monitoring [1, 2] which helps to model future changes. It aids in managing natural resources such as analyzing water resources, and vegetation, identifying areas with high biodiversity, forest cover, deforestation areas, and detecting fire-hazardous and burnout forest areas [3, 4]. Land use and land cover classification provides valuable information for agricultural planning and management It identifies crop types, and could be used for yield estimation and detecting agriculture changes [5]. Identifying and localizing possible risky Earth areas is used in developing efficient prevention solutions [6].

For further complex data, analysis, it is important to provide an image classification describing the observed land type. Accurate classification of land cover types enables correct decision making, supports sustainable development, and helps address various environmental challenges. Thus, the land use and land cover classification problem becomes a baseline one [7].

Deep learning (DL) approaches as a part of machine learning techniques have successfully contributed

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to various solutions and remain a popular choice for many complex tasks. Artificial neural networks learn features from the input data automatically, which is advantage compared with classical machine learning algorithms. It is known that the performance of classification systems depends on the amount of input data collected in datasets and labeled according to the predefined classes [8].

1.2 State of Art

Researchers [9] presented a patch-based land use and land cover classification approach using Sentinel-2 satellite images. The Sentinel-2 satellite images are openly and freely accessible. The dataset was published in 2019, geo-referenced, and collected from the Sentinel2 earth observation satellite multispectral mission. The image spatial resolution in the EuroSAT dataset varies from 60 to 10 m with 64x64 pixels size per image. An overall classification accuracy of 98.57 % was achieved with the proposed dataset.

In [10] authors classified a tree species composition of the Mozhariv forest for 20 years based on the Bayes classifier. The acquired satellite images are received from the satellites Landsat 5 and 8. These missions provide low-resolution images and could be considered in the analysis of huge surface areas. Such spatial resolution could be enough for environment analysis or vegetation classification, but the urban change classification is ineligible. Controversially, in [11] and [12], authors focus on a very high resolution (VHR) remotely sensed images. In [12] the image sizes are in the range of 800x800 to 4000x4000. These images were used for airplane detection (overall 1631 images that contained 5209 commercial airplane objects). The used R-CNN convolutional neural network showed acceptable results and better result metrics than the state-of-art detection YOLO-v3 model. Very high spatial resolution images could be naturally used for the object size and detection accuracy manner (as presented in [12] large- and medium-sized airplanes were detected with higher accuracy), such spatial resolution is overpriced for LULC classification tasks and leads to high compute resource consumption during training and validating classifiers. Therefore, in current research, we focus on high-resolution images (up to 3 m per pixel), so their spatial resolution is sufficient for classification tasks. Such data could be acquired frequently, and do not require huge amounts of RAM and computational resources.

1.3 The purpose and tasks of research

This study proposes a solution for the land cover and land use classification problem of high-resolution remote sensing data by applying deep learning methods based on a new EuroPlanet geo-referenced dataset. It consists of high-quality images with 4 spectral bands (R, G, B, and NIR), a spatial resolution of up to 3.125 m per pixel, and was acquired by the Planet platform in 2020-2022 years across the European region. Each image in the dataset has a size of 204x204 pixels.

To achieve this goal, we must solve the following tasks:

- acquire high-resolution quality images and form EuroPlanet dataset;
- develop and adjust the deep learning approach based on convolutional neural networks that is suitable for the LULC problem;
- improve model performance by providing bands evaluation of pre-calculated spectral indexes and train/test ratio.
- analyze the effectiveness of the developed method on the EuroPlanet dataset.

Structurally, the paper consists of the following sections. An analysis of classical remote sensing datasets, modern satellite image providers, and acquiring the EuroPlanet dataset is presented in Section 2. Section 3 describes convolutional neural networks and experiments setup. Section 4 contains a discussion of the obtained results. The last section provides the conclusions of the paper and directions for future research.

2. EuroPlanet Dataset Creation

2.1 Remote Sensing Classical Datasets

There are multiple classical remote sensing datasets (see Table 1) that are used for the creation, evaluation, and validation of different deep learning algorithms when solving land use, land cover, and related classification problems.

Table 1

Classical remote sensing datasets

No	Name	Bands	Number of images	Number of classes	Reference
1	UC Merced	RGB	2,100	21	[13]
2	RSSCN7	RGB	2,800	7	[14]
3	AID	RGB	10,000	30	[15]
4	RSI-CB	RGB	36,707	12	[16]
5	PatternNet	RGB	30,400	38	[17]
6	NWPU-RESISC45	RGB	31,500	45	[18]
7	EuroSAT	Multi-spectral	27,000	10	[12]

UC Merced dataset contains manually selected 21 classes (agricultural, forest, residential, buildings, etc.) of land-use images with 256x256 pixels each. It was generated from aerial ortho-imagery and downloaded from the United States Geological Survey (USGS) National Map. There are 2100 images. Such an amount of data makes the dataset the smallest one. NWPU-RESISC45 and PatternNet datasets are based on very high-resolution images (up to 30 cm/pixel). Because exceedingly high resources are needed to acquire, clean, and preprocess such datasets they have only a few hundred images per class. RSI-CB contains 45 categories and more than 36,000 images with up to 3 m spatial resolution, but it includes only 3 bands. Wuhan University presented the AID dataset which consists of 10,000 images (600x600 pixels) labeled in 30 classes. There are around 330 images in each category with spatial resolutions from 0.5 to 8 m per pixel. AID is larger than UC Merced, but the overall number of images is small.

Among considered above remote sensing classical datasets EuroSAT [12] is the most recent and unique from previous ones and it is multi-spectral, covering 13 spectral bands in the visible, near-infrared, and short-wave infrared parts of the spectrum. It consists of 27,000 images across 34 European countries: Austria, Belarus, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Macedonia, Malta, Republic of Moldova, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, and United Kingdom. The dataset is separated into 10 different classes with 2,000 to 3,000 images per class. The images size is 64x64 pixels, spatial resolution is up to 10 meters per pixel. EuroSAT dataset was successfully used for land cover and land use classification problems. Recently wetlands detection critical to ecology because of maintaining biodiversity identification was carried out in [19] based on part of the EuroSAT dataset. In [20] authors showed that adding additional spectral bands as input features in the convolutional neural network significantly increased the results and improved classification accuracy.

2.2 Modern satellite images providers

In the last decades, various programs and projects that provide satellite images have appeared. In general, these data sources are divided into commercial (Planet, Maxar) and free-of-use ones (Landsat, Sentinel2). The Landsat program was launched and supported by the National Aeronautics and Space Administration (NASA)/United States Geological Survey (USGS) which is a pioneer in acquiring remote sensing multispectral images. One of the most significant developments in the Landsat program over the past years has been the adoption of a free and open data policy. The program provides 30 m resolution multispectral data coverage that is used to monitor, understand, and manage the Earth's resources and terrestrial processes policy [21]. The Sentinel-2 satellite was launched by the European Commission and European Space Agency and covers multispectral images from 60 to 20 m per pixel. Despite Landsat supplies images in 11 different bands and global coverage approximately every three days, the Sentinel-2 Multi-Spectral Instrument features 13 spectral bands spanning from the visible and near-infrared (VNIR) to the short-wave infrared (SWIR), featuring 4 spectral bands at 10 m, 6 bands at 20 m and 3 bands at 60 m spatial resolution and 10 days minimum revisit time at the equator Aerosols, Cirrus and Water vapor bands could be used for the correction of atmospheric effects [20]. Higher image resolution allows us to perform more precise calculations. Although Landsat and Sentinel-2 programs' images are available for free the revisit time and spatial resolution are not enough for modern applications where high-resolution data could play a vital role in solving various issues.

The Maxar company suggests different commercial satellite types and provides the ability to search and download databases of satellite imagery and other geospatial products. For instance, WorldView-3 is the industry's first multi-payload, super-spectral, high-resolution commercial satellite. Operating at an altitude of 617 km, WorldView-3 provides 31 cm panchromatic resolution, 1.24 m multispectral resolution, 3.7 m short-wave infrared resolution, and 30 m CAVIS resolution. WorldView-3 has an average revisit time of less than one day and can collect up to 680,000 sq km per day [22]. Despite all the advantages mentioned above the company doesn't provide free access to satellite images and our available computing and storage resources don't align with very high-resolution images.

The Planet is one of the most known commercial projects that also provides daily satellite data and helps businesses, civil services, researchers, and journalists understand the physical world and take action. PlanetScope, operated by Planet, is a constellation of approximately 130 satellites, able to image the entire land surface of the Earth every day (a daily collection capacity of 200 million sq km day). PlanetScope images are approximately 3 m per pixel resolution. Among different PlanetScope assets, the PlanetScope Ortho Tiles products are radiometrically, sensor, and geometrically corrected and aligned to a cartographic map projection. The acquired images are divided into 25 km by 25 km tiles and based on a worldwide, fixed UTM grid system The grid is defined in 24 km by 24 km tile centres, with 1 km of overlap (each tile has an additional 500 m overlap with adjacent tiles), resulting in 25 km by 25 km tiles [23]. Each tile consists of 4 bands: red, green, blue, and near-infrared ones. The company provided the re-

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search account for the study with the ability to search and download PlanetScope Ortho Tiles assets.

2.3 Acquiring EuroPlanet Dataset

The EuroPlanet dataset is based on geo-referenced EuroSAT data acquired by the Planet platform in terms of PlanetScope Ortho Tiles assets. One of Planet's platform benefits is the ability to search metadata and get only high-quality images based on given geometries (see Fig. 1).

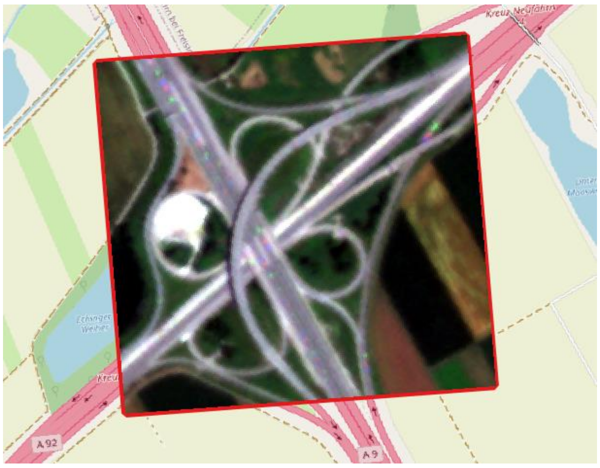

Fig. 1. Geo-referenced Highway image sample placed on OpenStreetMap near Munich, Germany with coordinates longitude: 48.3163; latitude: 11.6211

For instance, accurate and automated cloud detection provided by the Planet platform allows the filtering of images that don't meet a certain quality threshold. Before downloading the full image, the user can first preview it in .png format. For our case we have used the following constraints: clear, visible, and visible confidence parameters must be ≥95 % and cloud cover, shadow, and snow ice ≤2 %. The image-acquiring pipeline of satellite image collecting is shown in Fig. 2.

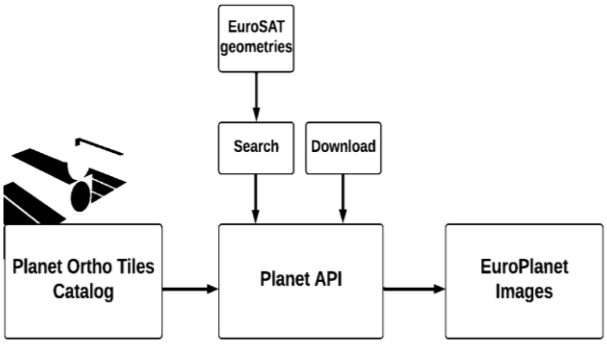

Fig. 2. Images acquiring pipeline

In comparison with the EuroSAT dataset (see Table 2) our image patches measure 204x204 pixels and represent 4 bands with a resolution of up to 3 m per pixel. The acquired date ranges from January 2020 to September 2022. The dataset consists of 25911 (that is 95.97 % from the original one) labeled images with ten different land use and land cover classes shown in Fig. 3.

Table 2

EuroSAT and EuroPlanet compression table

Parameter	EuroSAT	EuroPlanet
Image size	64x64	204x204
Spatial resolution	up to 10 m	up to 3 m
Number of images	27000	25911
Number of classes	10	10
Bands	13	4
Source	Sentinel-2	Planet

The image comparison between the EuroSAT and the proposed dataset is presented in Fig. 4. In our dataset, some of the images are rotated (see Fig. 5) because we were not post-processed them after downloading. The dataset is slightly imbalanced for Highway, Industrial, Pasture, Permanent Crop, and River classes.

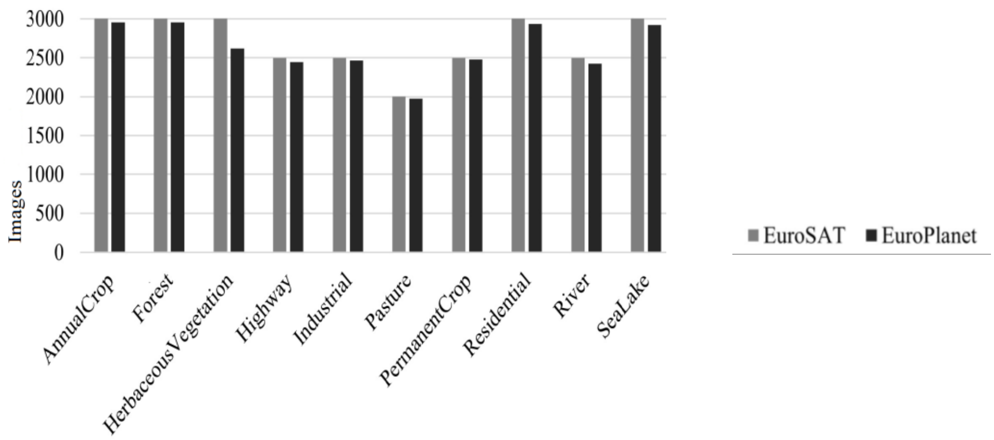

Fig. 3. EuroSAT and EuroPlanet classes distribution comparison

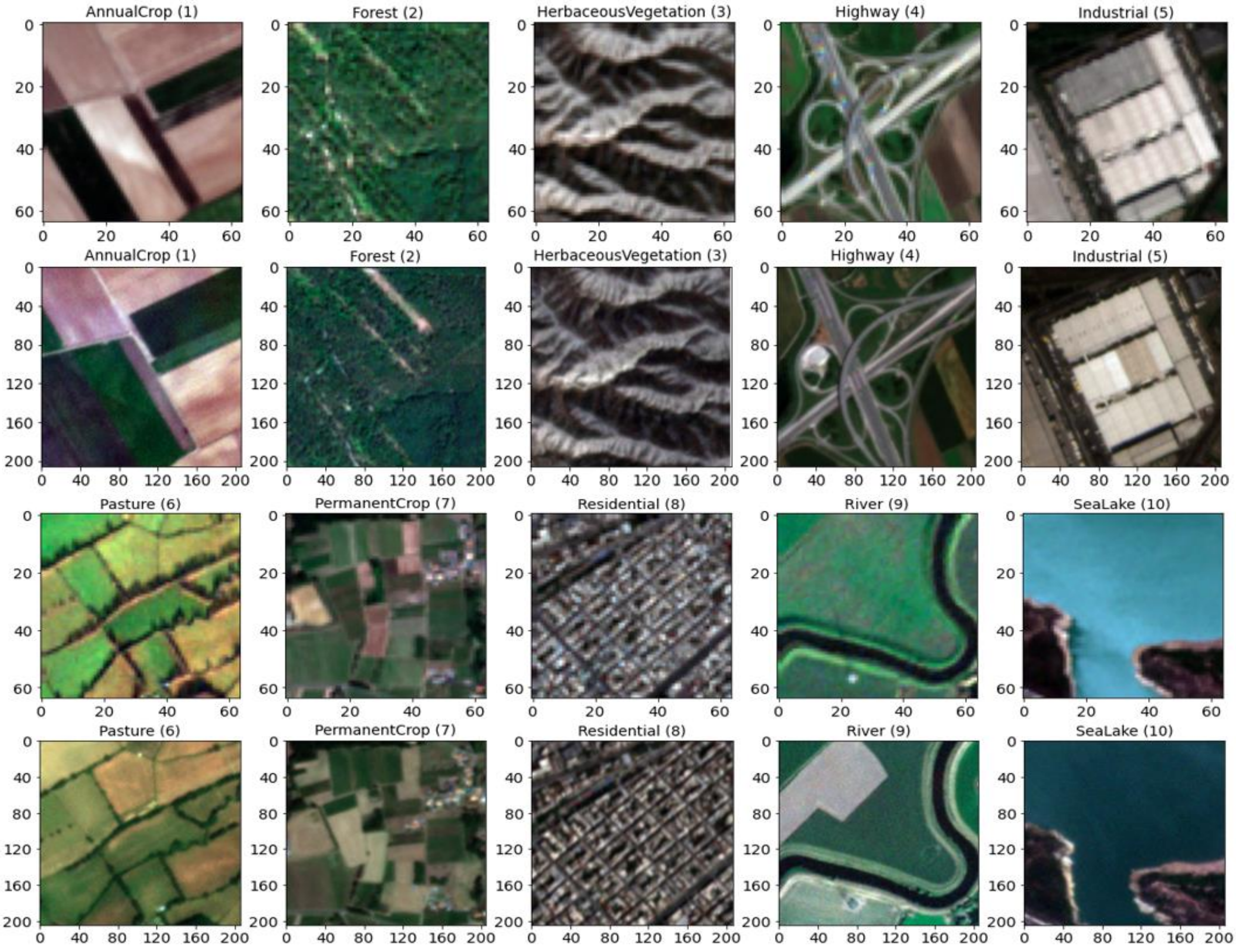

Fig. 4. Sample image resolution comparison. EuroSAT images measure 64x64 pixels and EuroPlanet 204x204 pixels. The images have the same geo-coordinates but were acquired in a different timeframe. The first and third rows represent the original EuroSAT dataset. The second and fourth rows represent EuroPlanet dataset

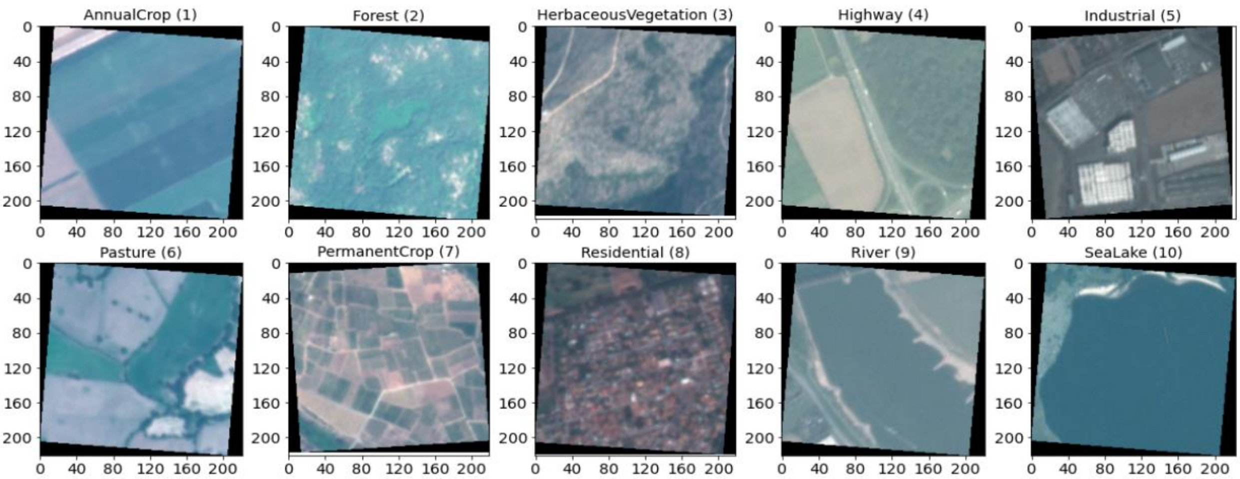

Fig. 5. EuroPlanet sample images resolution examples of unideal (rotated) images

3. EuroPlanet Dataset Evaluation

In the past decades, various remote sensing processing methods have been developed to improve the performance and accuracy of remote sensing solutions. Machine learning methods such as support vector machines and ensemble classifiers (e.g., random forest and gradient boosting) obtained high accuracies for such issues. Deep learning methods have recently become a central and state-of-the-art method for computer vision applications, remote sensing image processing and can automatically extract the required information from the

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input data [24]. These algorithms have been widely used and have shown promising results for change and object detection, and multispectral image classification. In different studies, the researchers use all available spatial information from satellite data that includes geo-coordinates, images with more than three classical RGB bands, etc to increase result metrics (for instance, classification accuracy) or improve models.

3.1 Convolutional Neural Networks

Among various deep learning approaches Convolutional neural networks (CNNs) are effective in remote sensing image classification and have been used for dataset benchmarking [9, 25]. These neural networks can extract features automatically compared with traditional image classification methods. Convolutional neural network architecture is made up of convolutional layers that determine the features, batch normalization layers, activation layers, and fully connected layer or layers for the classification of the input vector. The general form of the output vector for convolutional could be written as:

$$\mathrm{Conv}(k) = F\left(\sum_{i=1}^{n}\sum_{j=1}^{m} N_{(i,j)} \times W_{(i,j)} + b\right),$$

where F – is an activation function, $W_{(i,j)}$ is a weight corresponding to the i-th row and j-th column of the input vector $N_{(i,j)}$ and b – constant, which is added to the product of features and weights. In our case the vector $N_{(i,j)}$ represents input image.

Transfer learning improves a learner from one domain by transferring information from a related domain [26]. The technique is used for repurposing a model trained on one task to a comparable task that requires some adaptations. Deep neural network models must be trained with a huge number of parameters and this process requires a lot of resources. Transfer learning enables model parameters to start with good initial values that only need minimal tweaks to be better curated for the new problem [27].

The VGG-16 is a state of art convolutional neural network [28] initially introduced in 2014 for the ImageNet competition. It comprises 16 layers which consist of 13 convolution layers and three dense layers. The VGG-16 is classical one and shows high performance for image classification issues. It is designed to use small convolutional filters while increasing the depth of the neural network.

As the number of layers increases the network can process more complex features. On the other hand, training very deep neural networks requires more computational resources and causes a well-known vanishing gradient problem as the gradient could become too small. To solve this issue in [29], the authors suggested the Residual Neural Network (ResNet) that includes a skip connection, which transfers the inputs of the previous layer to the next layer. Such neural networks showed that increased depth can lead to a considerable boost in result accuracy. In [30] a new residual unit was proposed, which makes training easier and improves the generalization of such networks.

The Xception neural network is a convolutional neural network architecture based entirely on separable convolution layers. In [31] an interpretation of Inception modules in convolutional neural networks was presented, it was presented as being an intermediate step in-between regular convolution and the depthwise separable convolution operation. The Xception slightly outperforms Inception V3 on the ImageNet dataset and significantly outperforms Inception V3 on a larger image classification dataset. The performance gains are not due to increased capacity but rather to more efficient use of model parameters.

The idea behind a Dense Convolutional Network (DenseNet) [32] is based on direct connections between any two layers of a convolutional neural network with the same feature-map size. It is shown that DenseNets scale naturally to a large number of layers while exhibiting no optimization difficulties with increasing accuracy and without any signs of performance degradation or overfitting. Moreover, the authors showed that DenseNets require substantially fewer parameters and less computation to achieve state-of-the-art performances.

EfficientNetV2 was announced in 2021 [33]. This model represents a new family of smaller and faster neural networks for image recognition. EfficientNetV2 consumes fewer computational resources, and the training process is speeded up. In conducted experiments, the model outperforms previous efficient models, while being much faster. In addition, an improved method of progressive learning showed comparative performance on the classical ImageNet dataset.

In our study, we tested multiple state-of-art pretrained convolutional neural network families to serve as baseline models for the EuroPlanet dataset benchmarking (VGG-16, ResNet50v2, Xception, DenseNet201, and EfficientNetV2). In addition, we also evaluated the spectral bands, their combinations, and the train-test dataset split rate.

3.2 Experiments Setup

In this study, the EuroPlanet dataset is used for the land crop and land cover classification problem. The entire dataset was divided into 80 % training and 20 % test sets. The CNN pretrained models were trained and tested with a Google Collaboratory Pro+ integrated development environment [34]. It provides either Python runtimes with the essential deep learning libraries (including Keras) and GPU support. In our experiments, we used 40 GB NVIDIA A100 Tensor Core GPU processor and 85 GB RAM.

We have frozen convolutional layers and trained the top levels of each neural network to fine-tune the model to a new classification task. At the final stage of the neural network, a simple dense layer with 2500 neurons was added. For overfitting prevention, the dropout layer with a rate of 0.05 was used. The final layer represents 10 classes with softmax activation function. SGD learning algorithm with 1e-4 learning rate was selected. While training, we deployed EarlyStopping [35] with patience of 5 that monitored validation accuracy. Therefore the number of epochs varies for each experiment. Table 3 lists the training hyperparameters.

Table 3

Hyperparameters used in experiments

Hyperparameter	Value
Epochs	500
Learning rate	1e-4
Dropout	0.05
Dense neurons	2500
Activation	Softmax
Batch size	25
Loss	Categorical crossentropy
Optimizer	SGD

In supervised learning for classification problems, accuracy and F1 score (which represents the harmonic mean of precision and recall) are the main metrics that help evaluate model performance. They are defined as:

$$\mathrm{Acc} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}}, \quad F_1 = \frac{2\mathrm{TP}}{2\mathrm{TP}+\mathrm{FP}+\mathrm{FN}},$$

where a correctly classified positive sample is called (TP), classified as negative – false negative (FN). If the sample is negative and is classified as negative it is considered as true negative (TN); if it is classified as positive, it is counted as false positive (FP).

4. Results and Discussion

In this study, we have performed a set of experiments to evaluate the EuroPlanet dataset on various deep learning neural networks (VGG-16, ResNet50v2, Xception, DenseNet201, and EfficientNetV2). We considered overall accuracy and F1 score as performance metrics. Selected neural networks accept as input no more than three bands, so we have used Band 03 as a read, Band 02 as green, and Band 01 as a blue channel. The input shape was 204x204x3 with a test split portion of 20 %.

It is shown in Table 4 that all CNN models demonstrated classification accuracy and F1 score values under 90 %, except the DenseNet201 model which outperformed up to 2 % of other neural networks and reached 92.01 % for accuracy and 91.63 % for F1 score metrics. The training process for every epoch and classification accuracy of the training dataset for the selected set of pretrained convolutional neural networks is presented in Fig. 6.

Table 4

RGB EuroPlanet benchmark classification

Model	Accuracy, %	F1, %	Epochs	Time, sec
ResNet50v2	80.16	79.24	30	750
EfficientNetV2	84.08	83.39	77	2200
Xception	88.63	88.14	81	2010
VGG-16	89.81	89.41	224	5600
DenseNet201	**92.01**	**91.63**	77	2511

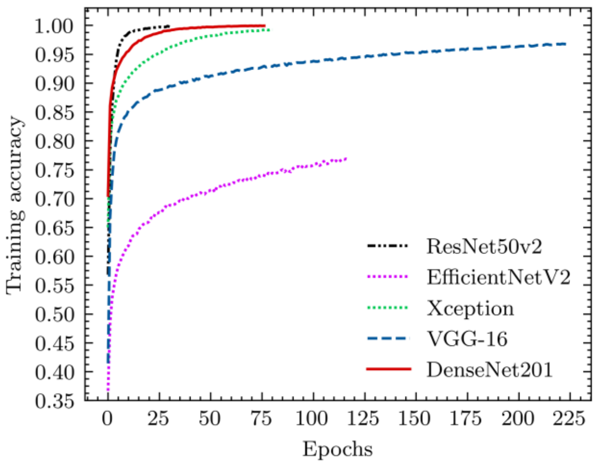

Fig. 6. EuroPlanet classification accuracy on training data

As mentioned above in the study the Planet platform provides 4 bands for Planet Ortho Tiles assets. Thus, it is useful to conduct band evaluation and analyze the performance of deep CNNs on a single band and their best combinations. Following the results that have been shown in [20, 36, 37] calculating and adding the spectral indexes as inputs in the models could strongly improve result metrics. For instance, in [20] it is shown that the combination of NDVI, NDWI, and GNDVI with RGB channels increased classification accuracy from 64.72 % to 84.19 % and F1 score from 63.89 % to 84.05 %. The authors in [38] presented evaluating different sets of spectral bands for the multispectral panoptic segmentation issue and found that adding spectral bands improved research results. Each EuroPlanet dataset sample consists of R, G, B, and NIR channels, and it is possible to calculate the Normalized Difference Vegetation Index (NDVI) [39] and Normal-

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ized Difference Green NDVI (GNDVI) [40] spectral indexes.

These indexes are defined as:

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}}, \quad GNDVI = \frac{\rho_{nir} - \rho_{green}}{\rho_{nir} + \rho_{green}},$$

where ρ_i – reflectance value of i-th band.

We have conducted single-band and band combination evaluations. In cases for the single-band image evaluation when the input channel has only one dimension, we passed the same data to all three inputs. According to the result obtained in the previous experiment, we have used DenseNet201 convolutional neural network as it had shown the best results. The train-test dataset split rate was 80/20 respectively. Table 5 represents the band's evaluation results. It had been found that for the EuroPlanet dataset and three-channel convolutional neural network the best indexes combination consists of Red, Green, and GNDVI bands. Such a set of inputs increased the F1 score from 91.63 % to 92.97 %.

Table 5

EuroPlanet bands evaluation on DenseNet201 model

Band/Combination	Accuracy, %	F1, %	Epochs	Time, sec
R	89.14	88.67	42	1410
G	90.22	89.85	35	1179
B	88.06	87.57	45	1510
NIR	89.00	88.12	52	1800
NDVI	88.69	88.40	38	1310
GNDVI	89.20	88.93	62	2120
NIR+NDVI+GNDVI	93.09	92.83	45	1550
R+G+GNDVI	**93.27**	**92.97**	51	1750

In addition to previous research, we have evaluated different train-test ratios (from 10 % to 90 % with the step of 10 %) on the EuroPlanet dataset. Furthermore, it was ensured that the split was applied class-wise by passing stratify parameter in the split function. The results are shown in Table 6. As we can observe fine-tuned DenseNet201 convolutional neural network achieved a classification accuracy of about 0.5 % higher compared to the previously randomly selected split.

The classification accuracy comparison for DenseNet201 neural network with different band combinations and train-test splits is presented in Fig. 7.

The graphs in Fig. 8 and 9 illustrate the training, validation classification accuracies, and loss value dependence on epochs for DenseNet201 fine-tuned neural network with RG+GNDVI bands combination and train-test split ratio of 0.1. The final test accuracy of the trained model was 93.83 % and the F1 score was 93.56 %.

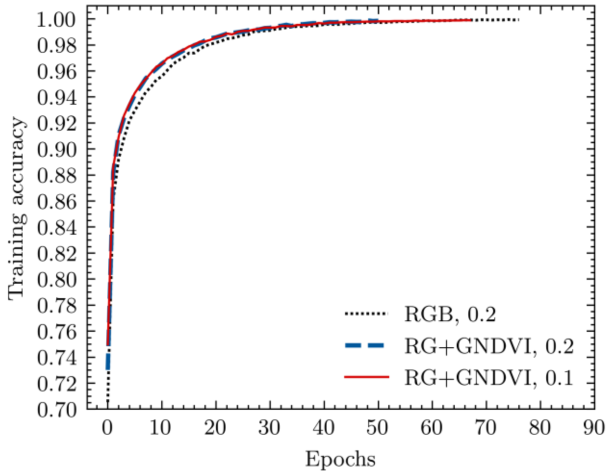

Fig. 7. DenseNet201 classification accuracy on training data for RGB, RG+GNDVI, and RG+GNDVI bands combination with different train-test split ratios

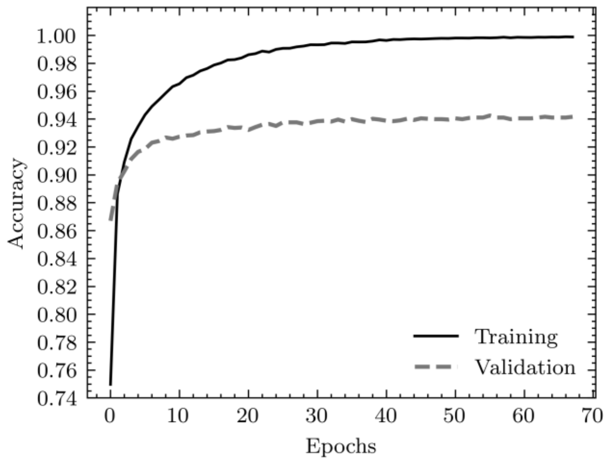

Fig. 8. DenseNet201 classification accuracy for RG+GNDVI and a train-test split ratio of 0.1

Table 6

EuroPlanet different test/train split evaluation (R+G+GNDVI) on DenseNet201 model

Metric	**10/90**	20/80	30/70	40/60	50/50	60/40	70/30	80/20	90/10
Accuracy, %	**93.83**	93.27	93.20	93.02	92.54	92.18	92.17	91.46	89.60
F1, %	**93.56**	92.97	92.88	92.76	92.24	91.88	91.77	90.91	88.63
Epochs	68	51	58	58	69	50	68	147	126
Time, sec	2530	1740	1730	1480	1430	870	860	1260	560

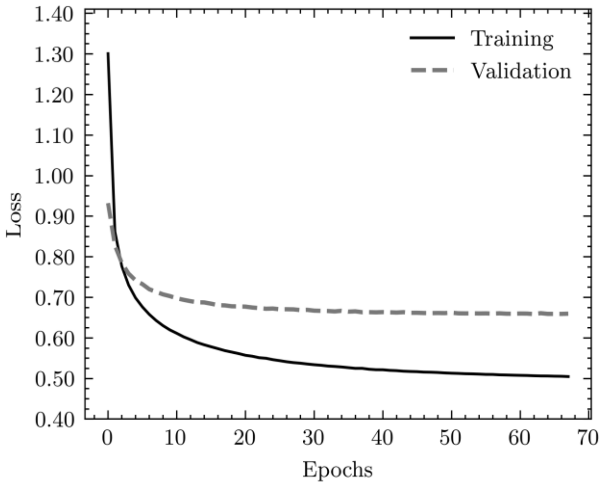

Fig. 9. DenseNet201 classification loss for RG+GNDVI and a train-test split ratio of 0.1.

An analysis of Table 7 illustrates the percentage improvement of the F1 score metric for each class in the EuroPlanet dataset. The neural network optimization process allowed a high increase the F1 score for River (95.27 %), Herbaceous Vegetation (95.55 %), Forest (98.85 %), Residential (91.74 %), and SeaLake (89.89 %) classes.

Table 7

Fine-tuned DenseNet201 F1 score for EuroPlanet dataset classes

No	Class	RGB, 0.2	R+G+ +GNDVI, 0.2	R+G+ +GNDVI, 0.1
1	River	91.92	94.40	95.27
2	Highway	88.27	90.29	90.16
3	PermanentCrop	96.66	96.92	95.88
4	Industrial	98.07	97.41	96.55
5	Herbaceous Vegetation	90.38	91.89	95.55
6	AnnualCrop	88.12	89.76	89.28
7	Pasture	92.31	92.67	92.42
8	Forest	96.57	97.83	98.85
9	Residential	90.00	89.96	91.74
10	SeaLake	84.02	88.52	89.89

Conclusions

In recent years, deep learning approaches have made remarkable development and have been used in almost every technological sphere to solve various issues. Acquiring large volumes of satellite images frequently and periodically through different providers, we can use the multispectral images for various applications such as urban development, environment monitoring (for instance, climate changes), fire hazardous forest areas detection, disaster detection, agriculture fields observation, and yield prediction. In this paper, we addressed one of the main issues in remote sensing of land use and land cover classification. The multispectral dataset called EuroPlanet is based on previously well-known EuroSAT dataset coordinates. Satellite images in the EuroPlanet dataset have a spatial resolution of up to 3.125 m per pixel and were acquired from 2020 to 2022 years. The dataset has 4 bands (R, G, B, and NIR) with 204x204 pixels per image. To obtain high-quality (having a low percentage of cloud, snow, etc) and high-resolution images, we used the Planet platform in terms of PlanetScope Ortho Tiles assets. The dataset consists of ten classes and includes 25 911 labeled images.

Among all deep learning approaches convolutional neural networks showed great performance in solving image classification tasks. Fine tuning helps to adapt previously designed and tested deep convolutional neural networks to new challenges and requires a lower number of computational resources and learning time. In the study, we provided a set of experiments for the EuroPlanet dataset with its spectral bands using state-of-the-art convolutional neural networks from different families (ResNet50v2, EfficientNetV2, Xception, VGG-16, and DenseNet201). It has been established that DenseNet201 pretrained neural network outperformed other models. The accuracy of the test data was 92.01 % and the F1 metric was 91.63 %.

In addition, we carried out a band combination evaluation. As a result, the RG+GNDVI showed the best performance and increased accuracy to 93.27 %. Final experiments with train-test split ratios improved the result metrics even more (from 92.01 % to 93.83 % and from 91.63 % to 93.56 % for classification accuracy and F1 score respectively). The EuroPlanet dataset can be used for an enormous range of applications (for instance, verification areas, identification, etc). Furthermore, it covers the Europe region and could be applied for real-time monitoring of surface changes. Solving such issues is highly needed to be solved because of the Russian invasion of Ukraine.

In future research, the additional performance evaluation and effectiveness of trained classifiers for land use and land cover classification based on EuroPlanet dataset will be provided. We expect that the trained DenseNet201 convolutional neural network will show acceptable classification results for the Ukrainian territory. Furthermore, the data augmentation technique can increase the diversity of the train dataset and make the classifier more stable for image transformations and rotations.

Contributions of authors: conceptualization – **Vladyslav Yaloveha**; methodology – **Vladyslav Yaloveha, Heorhii Kuchuk**; formulation of tasks – **Andrii Podorozhniak, Nataliia Garashchuk**;

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development of model, software – **Vladyslav Yaloveha, Andrii Podorozhniak**; analysis of results – **Vladyslav Yaloveha**, **Andrii Podorozhniak, Nataliia Garashchuk**; visualization – **Vladyslav Yaloveha**; writing – original draft preparation – **Andrii Podorozhniak, Vladyslav Yaloveha**; writing – review and editing – **Heorhii Kuchuk**, **Andrii Podorozhniak**.

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ПОРІВНЯННЯ ПРОДУКТИВНОСТІ CNN НА МУЛЬТИСПЕКТРАЛЬНИХ НАБОРАХ ДАНИХ ВИСОКОЇ РОЗДІЛЬНОСТІ ДЛЯ ПРОБЛЕМИ КЛАСИФІКАЦІЇ ЗЕМНОГО ПОКРИТТЯ

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Мультиспектральні зображення, отримані за допомогою супутників, використовуються в багатьох галузях, таких як сільське господарство, аналіз зміни місцевості, пошук пожежонебезпечних лісових територій і моніторинг земної поверхні в реальному часі. Класифікація земного покриття – це процес класифікації за визначеними класами на основі спектральних характеристик, отриманих із даних дистанційного зондування поверхні. Ця задача є непростою через складну природу поверхні Землі. Від якості даних дистанційного зондування земної поверхні, вибору алгоритму класифікації залежить точність вирішення задачі з використанням підходів глибокого навчання. Можливість періодично отримувати мультиспектральні зображення високої роздільної здатності може значно покращити рішення таких задач. У дослідженні пропонується розв’язок проблеми класифікації земельного покриву для даних дистанційного зондування з високою роздільною здатністю шляхом застосування методів глибокого навчання з використанням високоякісних зображень датасету EuroPlanet, що містить геодані, 4 різні мультиспектральні канали, зображення розміром 204x204 пікселів, отримані за допомогою платформи Planet у 2020-2022 роках. Набір даних складається з 25911 зображень з просторовою роздільною здатністю до 3,125 метрів на піксель із 10 різних класів. Для оцінки набору даних ми використовували попередньо навчені сучасні моделі згорткових нейронних мереж такі як ResNet50v2, EfficientNetV2, Xception, VGG-16 і DenseNet201. Встановлено, що попередньо навчена нейронна мережа DenseNet201 перевершила інші моделі. Точність класифікації на тестових даних склала 92,01 %, а метрика F1 – 91,63 %. Крім того, була проведена оцінка спектральних каналів для датасету EuroPlanet. Загальна точність класифікації склала 93,83 %, а F1 – 93,56 %. Результати дослідження можуть бути використані для аналізу земної поверхні, моніторингу в реальному часі та виявлення змін. Це дуже корисно використовувати для спостереження за територією України, зокрема і через російське вторгнення та відновлення країни в майбутньому.

Ключові слова: EuroPlanet; попередньо навчена нейронна мережа; мультиспектральні зображення; спектральні індекси; земельне покриття; дистанційне зондування.

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