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DEEP TRANSFER LEARNING OF SATELLITE IMAGERY FOR LAND USE AND LAND COVER CLASSIFICATION

Yifter T., Razoumny Yu., Lobanov V. **Deep Transfer Learning of Satellite Imagery for Land Use and Land Cover Classification.**

Abstract. Deep learning has been instrumental in solving difficult problems by automatically learning, from sample data, the rules (algorithms) that map an input to its respective output. Purpose: Perform land use landcover (LULC) classification using the training data of satellite imagery for Moscow region and compare the accuracy attained from different models. Methods: The accuracy attained for LULC classification using deep learning algorithm and satellite imagery data is dependent on both the model and the training dataset used. We have used state-of-the-art deep learning models and transfer learning, together with dataset appropriate for the models. Different methods were applied to fine tuning the models with different parameters and preparing the right dataset for training, including using data augmentation. Results: Four models of deep learning from Residual Network (ResNet) and Visual Geometry Group (VGG) namely: ResNet50, ResNet152, VGG16 and VGG19 has been used with transfer learning. Further training of the models is performed with training data collected from Sentinel-2 for the Moscow region and it is found that ResNet50 has given the highest accuracy for LULC classification for this region. Practical relevance: We have developed code that train the 4 models and make classification of the input image patches into one of the 10 classes (Annual Crop, Forest, Herbaceous Vegetation, Highway, Industrial, Pasture, Permanent Crop, Residential, River, and Sea&Lake).

Keywords: neural networks, deep transfer learning, land use land cover classification, satellite imagery.

1. Introduction. There is no doubt that soon artificial intelligence (AI) will penetrate every task that requires intelligent decisions based on learning from the collected data. It will change the way things are done, from language translation to self-driving cars and plenty of other tasks essential for a human being. It will have a remarkable effect on our day-to-day life. In recent years, AI’s success is accelerated by advancement in deep learning (DL), a subset of AI dealing with learning from experience or data [1].

There are several reasons why deep learning is spreading across many fields so fast now. The availability of big data collected so far allows preparing massive training datasets required for DL applications. The rapid improvement of hardware and software computer components has enabled scientists to solve problems that were not solvable a few years ago. Science and engineering topics that were taken by Ph.D. students to do their complete thesis now can be addressed with a few lines of code on a decent computing device. Datasets can be collected online, and state-of-the-art algorithms can be applied to the same data leading to different outputs [2].

Meanwhile, the advances in Earth observation (EO) technologies have significantly improved the spatial, spectral, and temporal resolution of remotely sensed imagery. These achievements have allowed satellites to collect big EO data on a global scale related to different application scenarios. Simultaneously, deep learning is outpacing the other machine learning techniques in LULC classification tasks on satellite images [2].

Preparing training datasets is arguably the most challenging step in any machine learning project. EO data's nature adds additional complexity to the process because of higher spectral and radiometric resolution and other specific issues such as cloud and atmospheric noise.

The emergence of Google Earth Engine (GEE), the first publicly available cloud platform for big EO data analysis, has enabled scientists to process and analyze geospatial data in a multi-petabyte catalog without solving technical issues related to big data [3, 4, 5].

The platform proved to be helpful in preparing experiment-ready images with masked clouds and cloud shadows, snow/ice, and low-quality pixels, which is necessary for almost all remote sensing-related studies [6]. The increasing attention to GEE from researchers is pictured in Figure 1. This data is retrieved from an abstract and citation database Scopus with a search query: (TITLE-ABS-KEY ("earth engine") AND TITLE-ABS-KEY (google) AND DOCTYPE (ar OR re) AND PUBYEAR < 2022. However, only 15 from 691 published works relate to deep learning, making DL-related applications with GEE an urgent research topic.

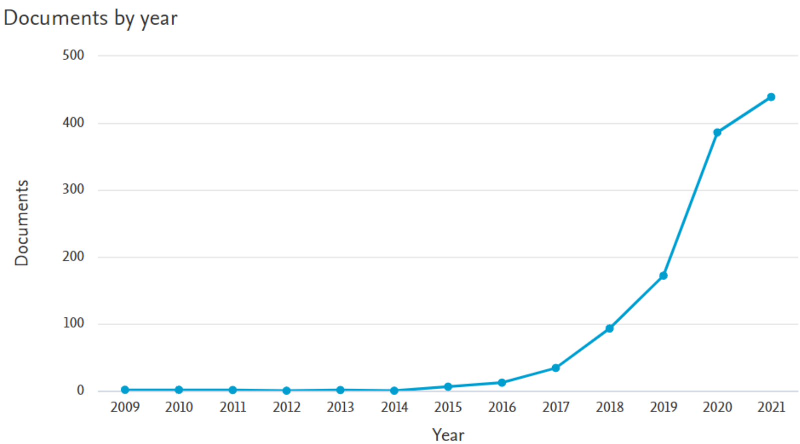


Fig. 1. Number of publications of the topic Deep Learning in Scopus

As it is complicated to construct large-scale well-annotated datasets due to the expense of data acquisition and labelling, a new DL approach called deep transfer learning (DTL) was developed allowing to solve the problem of insufficient training data. In DTL, the training data and test data are not required to be independent and identically distributed, and the target model does not need to be trained from scratch, which can significantly reduce the demand for training data and training time [7].

The technological advancements in both the data collection and processing have enabled a lot of new applications to pop up for solving real-world problems. The field of remote sensing has come a long way now to become very developed in collecting huge amounts of data that cover the entire earth and with continuous improvements in the quality of collected data. Even though different platforms can be used to collect remote sensing data, we are mainly focusing on data collected from satellites as it is the one which covers the entire earth. These huge continuously collected data have to be converted into insights to be useful for humanity. The complexity of the remotely sensed data hinders the extraction of insights out of it. Luckily, the advancement of technologies in the computing world has been a great motivation to process these huge data and extracting the right information at the right time. The recent development in Artificial Intelligence (AI) together with the progress made in the field of Computer Vision has given a lot of hope and hype for utilizing the remotely sensed data in different application areas. However, there is a gap between the continuously improving rate and quality of the collected data and its utilization for solving problems. This gap is a challenge, but at the same time, it is also an opportunity, that if the rate of utilization is improved, many difficult problems related to Agriculture, Climate, Environment, Economical and other areas will be tackled in an automated fashion.

The past decade has seen rapid progress in the capacity of DL especially for detecting objects from an image. In the state-of-the-art algorithms, the capability of DL has reached the human level, even better in some situations. But these DL algorithms cannot yield the same results when applied in remote sensing, and the reason for this is that there are some differences between these general image types and remote sensing images. So, there is a need to find the right approach for remote sensing data to benefit from the current achievement of DL in the general non-aerial image types. This approach requires understanding the spectral, spatial, and other characteristics of the remote sensing images, like texture.

With huge collected data and advancements in computational resources, remote sensing has become one of the beneficiaries of deep learning. At the same time, remote-sensing data presents some new challenges for deep learning, because satellite image analysis raises unique issues that pose difficult new scientific questions. The authors in [8] discuss the unique characteristics of remote sensing data saying that it comes from geodetic measurements with quality controls that are completely dependent on the adequacy of a sensor, and they are geo-located, time variable and usually multi-modal, i.e., captured jointly by different sensors with different contents. These characteristics raise new challenges on how to deal with the data that comes with a variety of impacting variables and may require prior knowledge about how it has been acquired. In addition, despite the fast-growing data volume on a global scale that contains plenty of metadata, it is lacking adequate annotations for direct use of supervised machine learning-based approaches. Therefore, to effectively employ machine learning and deep learning techniques on such data, additional efforts are needed. Moreover, in many cases, remote sensing is to retrieve geophysical and geochemical quantities rather than land cover classification and object detection, which [8] indicates that expert-free use of deep learning techniques is still getting questioned. Further challenges include limited resolution, high dimensionality, redundancy within data, atmospheric and acquisition noise, calibration of spectral bands, and many other source-specific issues [2, 8].

The success of the methods of DL in applications of remote sensing imagery depends on both the data and the used DL model. DL is a data-hungry process that thrives when there is a lot of training data. But there are many situations where it is very hard to get enough training data. In situations like this, data augmentation has been used to compensate for the lack of enough training samples [9].

One thing that we observed from our experiments is the importance of understanding the data itself. Even though the enhancements in the algorithms have improved the accuracy of training and testing, at some point it becomes stagnant that the model almost makes no progress at all. As a result, we concentrated our focus on the collected training data and we improved its quality by carefully selecting representative data and its results with an improvement in the accuracy of the detection.

The remote sensing methods of the Earth together with the development of the algorithms for processing them are the best combination to tackle problems that are affecting the Earth we live on. The relevance of these studies is associated with such challenges as climate change and predictions, analysis, and recognition of technical objects, infrastructure, preservation and development of environmental systems that is important for the global system of Society and ecology as well as for many other practical tasks.

With the Petabyte-scale images collected from satellites, information extraction could be challenging. Deep learning methods, which thrive in data-driven applications, can be the right tool to create insights out of this huge collected data. However, the methods require the laborious preparation of training datasets. The quality of the collected training data is as important as developing the right deep learning model for attaining high accuracy with the inferences [10]. This data-centric approach helps to make some accuracy gains. With this study, we tried to classify land use land cover in the Moscow region, by using a publicly available EuroSAT dataset. This dataset is created from European urban areas. The reason that we used this dataset is that there is a lot of similarity between the Moscow region and the European urban areas where this dataset is collected from.

In this paper, to create a LULC map of the Moscow region, we prepared a high-quality annotated test and validation datasets using satellite imagery in the Google Earth Engine platform. Based on the existing Earth observation datasets, we train state-of-the-art deep learning algorithms through transfer learning to distinguish between ten LULC classes. And in doing so, we made the following contributions:

– We introduce Moscow patch-based LULC classification dataset (MoscowSAT) based on Sentinel-2 satellite images. Every image in the dataset is labeled and geo-referenced.

– Four models of CNNs namely ResNet-50, ResNet-152, VGG16 and VGG19 were used with the datasets EuroSAT and MoscowSAT for training and testing respectively. Both datasets are from sentinel-2 red-green-blue (RGB) images.

– We have streamlined the models by tweaking the learning rate hyperparameter for the highest accuracy.

– The performances of the four models for classifying the 10 classes are displayed in the confusion matrix.

2. Literature review. Lately, after the introduction of neural networks for solving general computer vision problems, neural networks for satellite imagery have been included in the hot research topics. The reason being satellite imagery hosts a lot of information that is very important for solving problems that span a wide area of fields. Neural networks have proven to be very important tools for extracting insights from these huge collected data. Here we have mentioned some of the researches conducted on the diverse fields of applications.

Before the introduction of deep learning, other machine learning algorithms were applied to solve different problems. The algorithms Support Vector Machine (SVM) and Random Forest (RF) were the most successful classifiers of these types of algorithms [2]. Deep learning is different from these other machine learning algorithms in many ways. But we want to mention the two reasons that make it so popular. One of the reasons is that in the most problematic domains deep learning gives the highest classification accuracy, and the second reason is that it doesn't require manual feature extraction, and this enables end-to-end connections which automate feature extraction and perform the classification [2]. And as a result of its high accuracy and automation of almost the whole process of learning, it has been applied for solving problems in different application areas. Remote sensing has been applied successfully to a variety of classification and detection problems. The researchers in this study [11] presented an evaluation of fully convolutional neural networks (FCNNs) for road segmentation in satellite images. The authors' models show results, successfully extracting most of the roads in the test data set.

Detecting small objects such as vehicles in satellite images is a difficult problem. Deep convolutional neural networks (DNNs) can learn rich features from the training data automatically, and they have achieved state-of-the-art performance in many image classification databases. these authors [12] proposed a vehicle detection method in satellite images using a Deep Convolutional Neural Network(DNN). On a similar detection problem, these authors [13] present a hybrid DNN (HDNN) that HDNN significantly outperforms the traditional DNN for vehicle detection on satellite images. Still, with the problem of object detection, the authors of this paper [14] propose a new airport detection framework based on objectiveness detection techniques (e.g., BING) and Convolutional Neural Networks (CNN). Similarly, this work [15], proposed a method using convolutional neural networks (CNNs) for airport detection on optical satellite images.

Automatic object detection is a fundamental but challenging problem in the process of interpretation of satellite images. In this paper [16], an end-to-end multiscale convolutional neural network (MSCNN) is proposed, which is based on a unified multiscale backbone named EssNet for extracting features of diverse-scale objects in satellite images.

The paper on [17] describes a method for the effective semantic segmentation of satellite images and compares different object classifiers in terms of accuracy and execution time.

Very high resolution satellite imagery and image processing algorithms allow for the development of remote sensing applications. Recently, in addition to machine learning algorithms, deep learning methods have also been used to classify VHR images. In this paper [18], the authors compare the accuracy of the convolutional neural network (CNN) algorithm with some machine learning methods, for the classification of a satellite image with 50 cm spatial resolution.

Hyperspectral Satellite Images (HSI) present a rich spectrum of input data. In this paper [19], the authors propose an approach to the reduction and classification of HSI using dual Convolutional Neural Networks (DCNN).

Deep learning with satellite images provides a way to make predictions about the distribution of poverty. The work in this paper [20] results in a test accuracy of 76% for the three countries, whose satellite imagery is used in the research.

The work in this paper [21] aims to perform individual tree recognition on the basis of satellite images using deep learning approaches for northern temperate mixed forests in the Primorsky Region of the Russian Far East. Using U-Net-like CNN, they obtained a mean accuracy score of up to 0.96. A similar treetop detection proposed in this paper [22] introduces a framework using the automatically generated pseudo labels from unsupervised treetop detectors to train the CNNs, which saves manual labelling efforts.

A deep learning algorithm, the convolution neural network (CNN), was applied in this research [23] to rapidly extract road blockage information. The kappa coefficient and the F1 score of the results were 77.60% and 87.95%, respectively.

The success of applying a deep learning algorithm for solving problems is also dependent on the dataset collected for the purpose of training. This article [24] focuses on evaluating the available and public remote-sensing datasets and different techniques for satellite image classification, using Convolution Neural Networks (CNNs), precisely, AlexNet architecture with SVM classifier.

The authors of this paper [25] proposed an approach that can be used to extend the footprint of the high-resolution images to generate new time frames or to downscale the remote sensing imagery based on a distant but structurally similar training image. And in another domain, this paper presents [26], the technique of processing satellite images with their subsequent placement in cartographic services. There are many application areas where deep learning makes a big impact, and it keeps growing. It can be said that any problem domain that has a lot of data is suitable to be solved using deep learning.

3. Materials and Methods. This work has utilized the result achieved by the authors [27], in which they have created a dataset based on Sentinel-2 satellite images covering 13 spectral bands constituting (Table 1) 10 classes with in total of 27,000 labeled and geo-referenced images. They provided benchmarks for this dataset with its spectral bands using state-of-the-art deep Convolutional Neural Networks (CNNs) and with the proposed dataset, they achieved an overall classification accuracy of 98.57%.

Table 1. Sentinel-2 RGB bands and parameters

Sentinel-2 Band	Center Wavelength(nm)	Spectral Width(nm)	Spatial Resolution(m)
Band 2-Blue	490	65	10
Band 3-Green	560	35	10
Band 4-Red	665	30	10

The free availability of continuous Earth observation satellite data has motivated the processing of the data for some insights. This data processing has resulted in devising solutions to wide area domains including agriculture, environment, urban planning and disaster recovery. One part of the processing involves creating structured semantics out of the data, which is fundamental to creating LULC Classification [28].

LULC classification is an important task that enables us to understand the relationship between humans and the environment. Land Cover refers to the physical characteristics of the Earth’s surface, such as vegetation, water, and soil, while Land Use refers to the purposes for which humans exploit the Land Cover such as changes made by anthropogenic activities [29, 30]. Therefore, the aim of LULC classification is to automatically provide labels describing the represented physical land type or how a land area is used. LULC changes (LULCC) are a very important measurement for monitoring man-made changes (e.g., deforestation, urbanization, and agriculture intensification) or natural phenomenon (e.g., droughts, floods, and natural fires). Therefore, LULC data enables the creation of detailed mappings to enable sustainable development [29].

A. Study Area and Data. The test data for this study is collected from the Moscow region, Russia (Figure 2). This area is selected for the reason of applying the EuroSAT dataset as training data, which is created from European urban areas and using the MoscowSAT as a test area. Since the Moscow region is on the European side of Russia, we want to investigate how well the training dataset of EuroSAT fits to the collected testing dataset from the Moscow region.

Fig. 2. Region of Interest (ROI) of the study – Moscow region, Russia

To perform this task, we utilize the results achieved by [27] and apply them to the case of the Moscow region. And to keep everything similar between the 2 datasets, we have used the same classes for the classification. The LULC classes used in this study are Annual Crop, Forest, Herbaceous Vegetation, Highway, Industrial, Pasture, Permanent Crop, Residential, River, and Sea&Lake.

Generating labelled datasets requires manual work. We created the test dataset first by gathering satellite images of the Moscow region from Sentinel-2 and then, we created a dataset of 2,000 georeferenced and labeled image patches, representing the 10 classes that we sought to classify. The image patches measure 64x64 pixels and have been manually checked.

The Sentinel-2 is one of the satellites under the European Space Agency (ESA) Earth observation mission. ESA has made the continuously collected satellite images freely available within its Copernicus program. Besides this, sentinel-2 imagery is preferable for our task of LULC classification for the following reasons: (1) This satellite image has 13 bands obtained from the MSI (Multispectral Imager) instrument, (2) Temporal resolution of Sentinel-2 is 10 days performed by one satellite and 5 days performed with two satellites that will make large amounts of observational data available. This satellite has a spatial resolution from 10 to 60 m. The satellite image is composed of the following bands 4 (red), bands 3 (green), bands 2 (blue), bands 8 (Near-Infrared) and bands 11 (SWIR, Short-Wave Infrared). Band 4 is useful for identifying types of vegetation, soil and urban features; band 3 provides excellent contrast between clear and turbid (muddy) water; band 2 is useful for land and vegetation identification, forest type mapping, and identifying human-made features; while band 11 is useful for measuring soil moisture and vegetation, and it provides good contrast between various types of vegetation.

B. Deep transfer learning for image classification. In this study, we have used state-of-the-art deep learning algorithms with transfer learning (Figure 3) for finding the optimal algorithm that gives high accuracy. This is implemented using a jupyter notebook equipped with a TensorFlow GPU computing environment. We have used "Differential learning rates", which means different learning rates for different parts of the network during our training. The purpose of this is to divide the layers into various layer groups and set different learning rates for each group so that we get the best results.

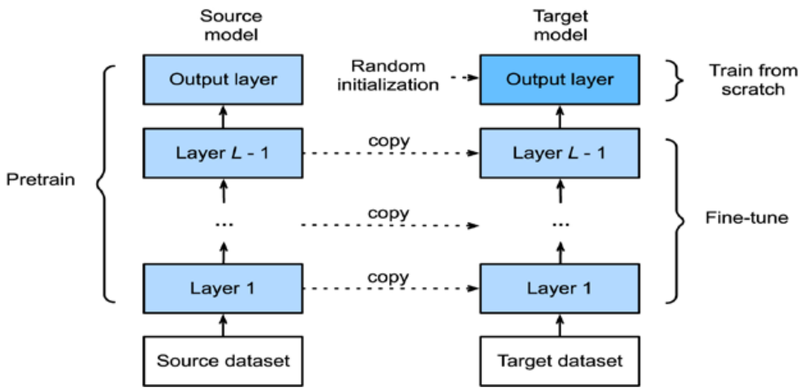


Fig. 3. Transfer Learning

This study used a supervised approach – creating training samples from input images as an automatic classification process. The final result of this process is a labeled dataset for training a classifier. The process starts by collecting data and ends by making predictions of the data into its respective classes. This process is depicted in Figure 4. And from the process implementation side, it can be summarized as: loading data from hard disk, data splitting into training and testing dataset, training CNN model, and evaluating model performance.

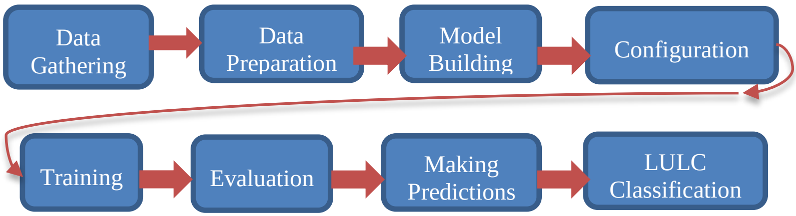


Fig. 4. Training process of the LULC classification

We divided the dataset into a training set (80%), validation set (10%) and test set (10%), in order to perform the training, validation and testing, respectively. We have used ResaNet 50 with transfer learning to train the model. This artificial neural network is basically composed of a 7×7 convolutional layer with 64 output channels and a stride of 2 followed by the 3×3 maximum pooling layer with a stride of 2. The batch normalization layer is added after each convolutional layer. Finally, the layers are preceded by one Flatten Layer, two Dense Layers and a Softmax Layer. The model architecture is depicted in Figure 5.

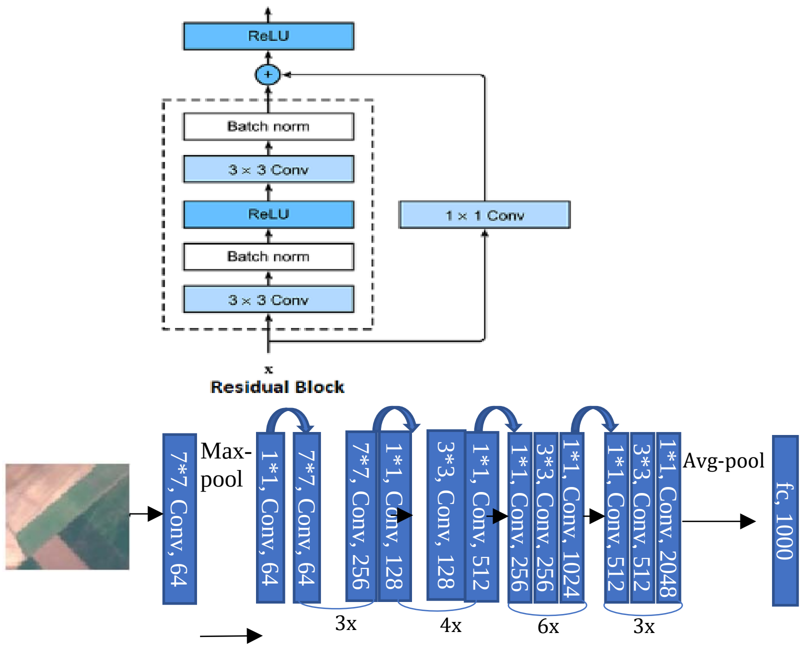
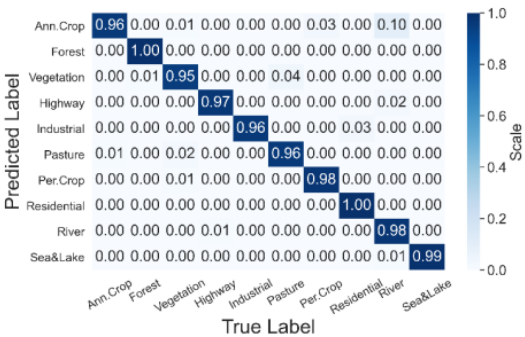


Fig. 5. ResNet 50 Model Architecture

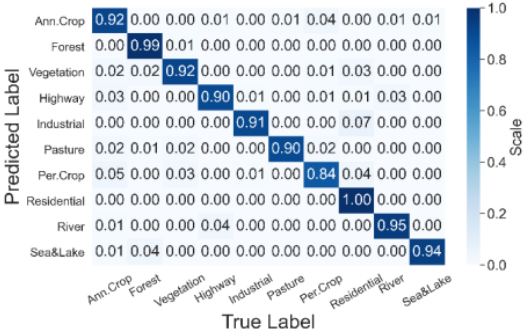
4. Results and Discussion. We run the classification algorithms ResNet 50, ResNet 152, VGG 16 and VGG 19 with transfer learning using the EuroSAT dataset and then continue training models with MoscowSAT dataset for the specifics related to the Moscow region. The used model and the dataset are crucial to achieving high accuracy. We have carefully created the MoscowSAT dataset to reflect the ground truth so that this part of the learning will be specific for the region. The results of our code analysis in the confusion matrix are displayed in Figure 6 from *a* to *d*. The confusion matrix is the results of the fine tunned training on the test dataset MoscowSAT using satellite images in the RGB color space. We discovered that ResNet 50 gives the highest accuracy, which is 98% in the training and 97.5% in the testing. As can be seen in the confusion matrix, there was high precision for almost all of the classes except there was some miss classification between permanent and annual crops (Figure 7). The comparison of the results of the three NN algorithms used is displayed in Table 2.

Table 2. Comparison of accuracy

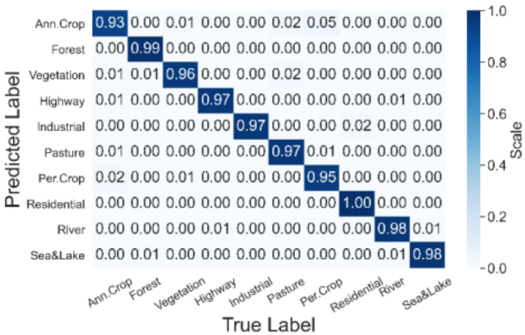
	ResNet50	ResNet152	VGG16	VGG19
Accuracy	0.975292588	0.932193944	0.952134497	0.968265



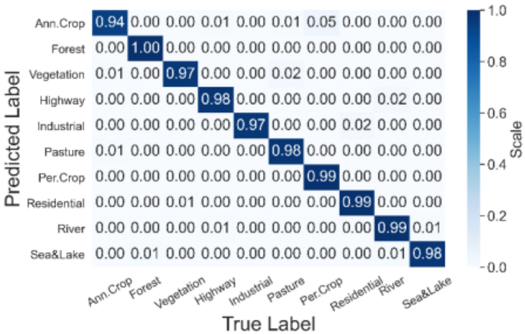
a) ResNet-50



b) ResNet-152



c) VGG 16



d) VGG 19

Fig. 6. Results of the fine tunned training on the test dataset MoscowSAT using satellite images in the RGB color space

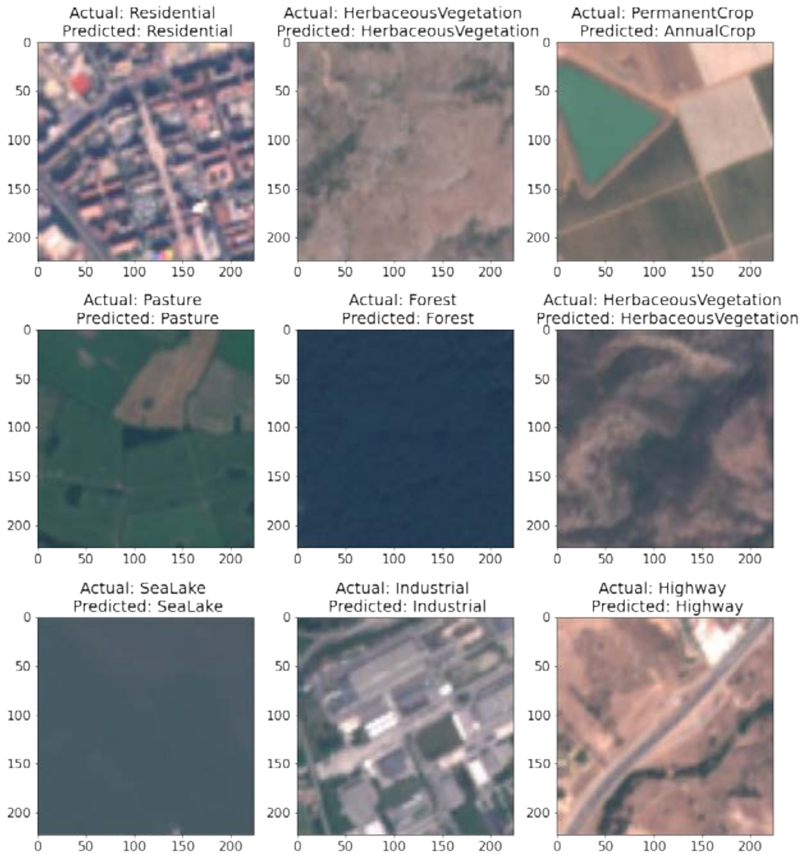


Fig. 7. ResNet-50 sample prediction output. The text displays the actual and predicted levels of each image. The permanent crop is confused with annual crop in this sample output

5. Conclusion. Regional land use planning and monitoring remain to be an important process that enables appropriate and optimal usage of resources. Despite many proposed models in the studies, the task remained a challenging problem. In this paper, we have used transfer learning of deep learning models for creating LULC of the Moscow region. We have fine-tuned 4 models of CNN, namely ResNet50, ResNet152, VGG16 and VGG19 with transfer learning and adjusting the learning rate for the optimal accuracy.

In general, our study is tailored toward creating the right tools to automate the extraction of information from satellite imagery. We have demonstrated the capability of remote sensing data together with deep learning for solving real-world problems. We achieved this by working towards creating the LULC Classification of the Moscow region. This study presented the results of LULC classification using Sentinel-2 satellite RGB imagery as input, the CNN model as the classifier, and the Moscow region area as the location for this study. The results showed that the ResNet50 CNN model together with transfer learning achieved high accuracy in classifying the 10 classes.

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ГЛУБОКОЕ ТРАНСФЕРНОЕ ОБУЧЕНИЕ НА ОСНОВЕ СПУТНИКОВЫХ ИЗОБРАЖЕНИЙ ДЛЯ КЛАССИФИКАЦИИ ЗЕМЛЕПОЛЬЗОВАНИЯ И ЗЕМНОГО ПОКРОВА

Уифтер Т.Т., Разумный Ю.Н., Лобанов В.К. **Глубокое трансферное обучение на основе спутниковых изображений для классификации землепользования и земного покрова.**

Аннотация. Алгоритмы глубокого обучения сыграли важную роль в решении многих комплексных задач, за счет автоматического изучения правил (алгоритмов) на основе выборочных данных, которые затем сопоставляют входные данные с соответствующими выходными данными. Цель работы: выполнить классификацию земных покровов (LULC) спутниковых снимков Московской области на основе обучающих данных и сравнить точность классификации, полученной с применением ряда моделей глубокого обучения. Методы: точность, достигаемая при классификации земных покровов с использованием алгоритмов глубокого обучения и данных космической съёмки, зависит как от конкретной модели глубокого обучения, так и от используемой обучающей выборки. Мы использовали наиболее современные модели глубокого обучения и обучения с подкреплением вкупе с релевантным набором обучающих данных. Для тонкой корректировки параметров моделей и подготовки обучающего набора данных применялись разливные методы, в том числе аугментация данных. Результаты: Применены четыре модели глубокого обучения на основе архитектур Residual Network (ResNet) и Visual Geometry Group (VGG) на основе обучения с подкреплением: ResNet50, ResNet152, VGG16 и VGG19. Последующее дообучение моделей выполнялось с использованием обучающих данных, собранных спутником ДЗЗ Sentinel-2 на территории Московской области. На основе оценки результатов, архитектура ResNet50 дала наиболее высокую точность классификации земных покровов на территории выбранного региона. Практическая значимость: авторы разработали алгоритм обучения четырёх моделей глубокого обучения с последующей классификацией фрагментов входного космического снимка с присвоением одного из 10 классов (однолетние культуры, лесной покров, травянистая растительность, автодороги и шоссе, промышленная застройка, пастбища, многолетние культуры, жилая застройка, реки и озера).

Ключевые слова: нейронные сети, глубокое трансферное обучение, классификация землепользования, спутниковые снимки.

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