International Journal of Applied Mathematics, Electronics and Computers 9(4): 091-096, 2021

e-ISSN: 2147-8228

INTERNATIONAL JOURNAL OF APPLIED MATHEMATICS ELECTRONICS AND COMPUTERS

www.dergipark.org.tr/ijamec

International Open Access

Volume 09
Issue 04

December,2021

Research Article

The Genus-Level Identification of Leaf Beetles (Coleoptera: Chrysomelidae) From Habitus Images with Convolutional Neural Network Classification

Mahmut Tokmak, [a,*] ***, İsmail Şen*** [b]

[a] *Isparta University of Applied Sciences, Gelendost Vocational School, Gelendost, 32900, Isparta, Türkiye*

[b] *Isparta University of Applied Sciences, Technology Faculty, Department of Biomedical Engineering, Çünür, 32260, Isparta, Türkiye*

ARTICLE INFO

Article history:
Received 1 September 2021
Accepted 12 November 2021

Keywords:
insect
systematic
machine learning
convolutional neural network
habitus image
image-based identification

ABSTRACT

Identifying an organism requires taxonomic expertise, time, and often adult specimens of that organism. Accurate identification of organisms is of great importance for sustainable agriculture, forestry and fisheries, combating pests and human diseases, disaster management, sustainable trade of biological products and management of alien invasive species. Advances in machine learning techniques have paved the way for the identification of animals by image analysis. In this context, it is aimed to test the success of different convolutional neural network (CNN) models in classifying leaf beetle (Coleoptera: Chrysomelidae) dorsal habitus images at the genus level. In this study, a total of 888 habitus images belonging to 17 genera were obtained from a website on leaf beetles and five CNN models (ResNet-152, Alex-Net, DenseNet-201, VGG-16 and MobileNet-V2) were used to classify leaf beetle genera. Also, the classification performance of the models was compared. The most successful model was ResNet-152 with an accuracy rate of 97.74%. These results showed that Resnet-152 can be used to identify European leaf beetle genera. As a result of this study, it was concluded that as the number of images increases, the identification of leaf beetles at the genus level can be made more easily by using CNNs.

1. Introduction

Systematic (taxonomy) is a scientific discipline that not only collects and identifies existing species and creates robust classifications by describing and naming new species, but also studies biological variations, biogeography and phylogeny [1, 2]. It is the most fundamental research area for all biological science and its application [3]. Accurate identification of organisms is of great importance for sustainable agriculture, forestry and fisheries, combating pests and human diseases, disaster management, sustainable trade of biological products and management of alien invasive species [4]. Thus universities, museums, and herbariums, as well as biosecurity, agriculture and forestry, pharmaceutical companies, and other disciplines, need systematists (taxomists) who can do definite systematic studies, especially species identification [5]. Agricultural and forest pests can cause serious damages to their hosts. Thus, they must be correctly and rapidly identified in order for them to be controlled [6, 7, 8]. Species identification by using morphological characters requires taxonomical expertise, time, and generally specimens of the adult stage of the organisms (especially of insects) [9]. Therefore, such studies are time-consuming and expensive [10]. These difficulties and wide-ranging needs have led to the effort to develop methods that can make rapid and expert-independent species identification. In 2003, a DNA-based

* Corresponding author. E-mail address: mahmuttokmak@isparta.edu.tr
DOI: 10.18100/ijamec.989263

barcoding system studying with the COI (cytochrome c oxidase I) sequences was suggested as an accurate, cost-effective, and accessible system for the identification of animals [11]. Even though this method is very useful, it requires a laboratory, and all of the described species are not hitherto barcoded [12, 13]. Another method that has been studied in recent years is classifying specimens according to image analysis [14].

Developments in machine learning have paved the way for species identification with image analysis. Deep learning is a form of machine learning that can perform a task without being specifically programmed to solve it. Instead, it develops computational models from previous examples of the specific task by using multiple processing layers thanks to the process called training. After training, the task can be performed on new data in a process called inference [15]. There is so much study to make automated species identification by using deep learning in the last years [15, 16]. In these studies, it has been revealed that successful results have been obtained in various pattern recognition areas, from image processing to voice recognition, with convolutional neural network (CNN) models, which is one of the deep learning methods. CNN is also used in species identification as a deep learning method, which is widely used in image segmentation, pattern recognition, and classification processes [17].

The number of insect species in the world is around one million [18]. The identification of the insects is very challenging not only because of their high number but also because of their different colors and shapes [19]. A highly diverse family among the insects is leaf beetles with about 37.000 species all over the world [20]. Adults and larvae of many leaf beetles have been accepted as pests in agricultural and forest areas [21]. Thus, there are some DNA-based studies to fast and accurate identification of the leaf beetles, especially Alticini species [22, 23]. There is no study on the identification of leaf beetles with machine learning techniques. In this context, it is aimed to test the success of different CNN models in classifying leaf beetle (Coleoptera: Chrysomelidae) dorsal habitus images at the genus level.

2. Materials and Methods

2.1. Leaf beetle dataset

The leaf beetle images used in this study were obtained from the website [24] prepared on European leaf beetles (Figure1). The dataset consists of 888 habitus images of 17 leaf beetle genera from which 9-142 samples for each genus. The detailed information for the dataset is given in Table 1. Some images had two habitus and/or male genitalia. All images had been arranged to have only one habitus per image. No more extra processing has been done on the images because they were already preprocessed. These genera were used because they are widely distributed in Europe and have plenty number of habitus images.

Table 1. Taxonomic classification of studied leaf beetle genera and the number of images (n) of each genus.

Subfamilia	Tribus	Genus	n
Galerucinae	Alticini	*Altica*	23
		Aphthona	56
		Asiorestia	27
		Chaetocnema	31
		Dibolia	18
		Epitrix	9
		Longitarsus	142
		Orestia	15
		Phyllotreta	61
		Psylliodes	69
	Luperini	*Luperus*	32
Chrysomelinae	Chrysomelini	*Chrysolina*	128
	Timarchini	*Timarcha*	41
Cryptocephalinae	Clytrini	*Labidostomis*	45
		Smaragdina	25
	Cryptocephalini	*Cryptocephalus*	115
		Pachybrachis	51
		Total	888

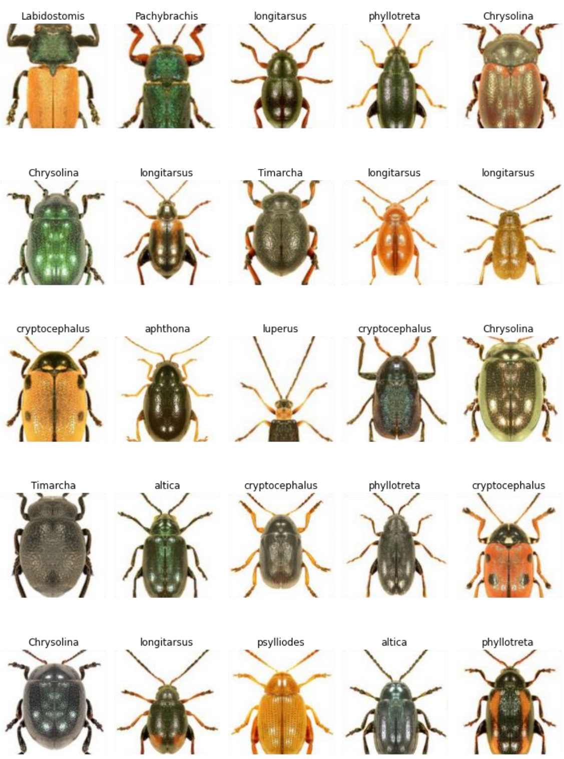

Figure 1. Samples of the habitus images belonging to leaf beetle genera in the dataset

2.2. Insect classification with convolutional neural network

2.2.1. Leaf beetle classification

CNN is similar to traditional artificial neural networks in that it consists of neurons that optimize themselves through learning and is a type of multi-layer perceptrons. A CNN consists of the input layer, the exit layer, and multiple hidden layers. Hidden layers typically consist of convolutional layer, pooling layer, fully connected layer and normalization layers (normalization layer, ReLU). Additional layers can be used for more complex models [25, 26]. A general CNN is shown in Figure 2.

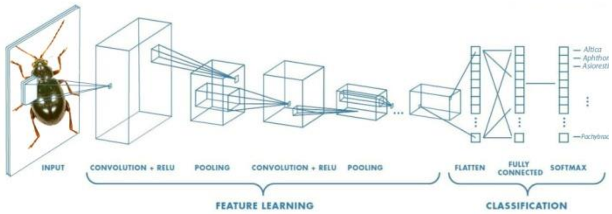

Figure 2. A general CNN architecture

The leaf beetles were classified by using a convolutional network which has recently become the widely used model in visual-based algorithms [15, 16, 27]. In the present study five CNN were used: a) Alex-Net b) VGG-16, c) ResNet-152, d) DenseNet-201, and e) mobilenet-V2.

a) AlexNet: The main layers of the AlexNet architecture are convolution, pooling and fully connected layers. The entire image is circulated by selecting filters (3×3 or 5×5) in the convolution layer. The image obtained as a result of the filtering is used by the next layer as the input image. Activation maps are created with the images passed by convolution layers. Activation maps are unique as they are produced based on input data. The pooling layer both reduces the input dimensions and retains the image features. Thus, the number of parameters of the model is reduced [26, 28, 29, 30, 31].

b) VGG-16: VGG-16 architecture totally consists of 21 main layers formed from convolution, pooling, and fully connected layers. VGG-16 has increasing network architecture. The filter size in the convolutional layer is 3×3 pixels. Layers that perform many operations are sequentially placed in a convolutional part of the network to learn the discriminative features from the input data. At the end of the architecture, the softmax layer is used as a classifier and the number of the output of the softmax layer is set as the same as our class number [32].

c) ResNet-152: ResNet has a structure called a residual learning unit which decreases the degradation of deep neural networks. This unit's structure is a feed forward network with a shortcut connection that adds new inputs into the network and generates new outputs. The main merit of this unit is that it produces better classification accuracy without increasing the complexity of the model [33].

d) DenseNet-201: The value added to a model in both layers in ResNet is added to all layers that follow it in DenseNet. This system has brought many advantages to the model. This made the network more easily trainable and optimized the problem of most layers being dysfunctional in high-tier networks [34].

e) MobileNet-V2: MobileNet aims to develop deep learning applications in mobile and embedded systems with fewer training parameters [35]. MobileNet architecture uses Depthwise Separable Convolutions technique in the feature extraction step. Thanks to this technique, feature extraction can be performed with fewer parameters than the standard convolution process. After the MobileNet architecture was developed, updates were made to be faster and more efficient, and MobileNet V2 was recommended. The size of the feature maps has been narrowed by using $1x1$ convolutions in MobileNet V2. In addition, thanks to the skip connection technique, which is also used in ResNET architectures, a faster calculation process has been provided [36].

2.2.2. Training and testing of neural networks and evaluating predictions

Google Colaboratory or shortly Colab cloud system was used on the training and testing of CNN. This system can perform a lot of calculations on big data quickly with the "NVIDIA Tesla K80 GPU", and has many Python and deep learning libraries ready in it. Also, this system is free of charge [37]. Fast.ai library was used for the training and testing of the models used in the study [38]. The dataset consisted of habitus images belonging to 888 species from 17 leaf beetle genera. Habitus images belonging to each genus were divided into two groups for training (80%) and testing (20%) the network, respectively. For the input data, the batch_size parameter is set to 32, validation_split parameter is set to 0.2 and the epoch value used in the model is set to 50. True positive (TP), false positive (FP), true negative (TN), false negative (FN) were calculated from all test habitus images for each genus. The success of the established models was calculated by using the results of these calculations with the following formulas.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - Score = \frac{2xSensitivityxPrecision}{Sensitivity + Precision} \quad (4)$$

$$TPR = \frac{TP}{FN + TP} \quad (5)$$

$$FPR = \frac{FP}{FP + TN} \quad (6)$$

3. Results

At the end of the study, the neural network, which classifies the data most successfully, was ResNet-152. While the accuracy of ResNet-152 was 97.74%, the accuracy of DenseNet-201, MobileNet-V2, AlexNet and VGG-16 were 94.25%, 96.61%, 95.48% and 94.35, respectively (Table 2 and Figure 3). ResNet-152 correctly predicted the genus of the 173 (97.74%) of the 177 test images. For ResNet-152 predictions on genus level, mean classification precision, recall and f1 score were 98.3%, 97.8% and 97.9%, respectively (Table 2).

Table 2. Model performance metrics

	Precision	Recall	F1-score	Accuracy
VGG-16	0.9458	0.9251	0.9324	0.9435
AlexNet	0.9563	0.9391	0.9412	0.9435
MobileNet-V2	0.9550	0.9471	0.9448	0.9548
DenseNet-201	0.9798	0.9617	0.9678	0.9661
ResNet-152	**0.9830**	**0.9780**	**0.9790**	**0.9774**

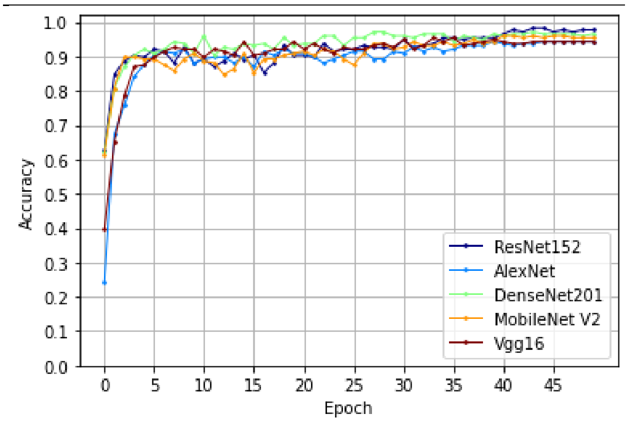

Figure3. Accuracy graph of the studied CNN models

According to genus-level predictions of ResNet-152, the confusion matrix of ResNet-152 in Figure 4 revealed that genera were often confused with other genera within the same tribus or sister tribus in the same subfamilia. The confusions in Alticini were among the *Aphthona* and *Altica*, and also *Longitarsus* and *Psylliodes*. The confusion in Clytrini was between *Smaragdina* and *Labidostomis*. The last confusion was also between tribes under Galerucinae: Alticini genus (*Longitarsus*) was mistakenly classified as Luperini (*Luperus*).

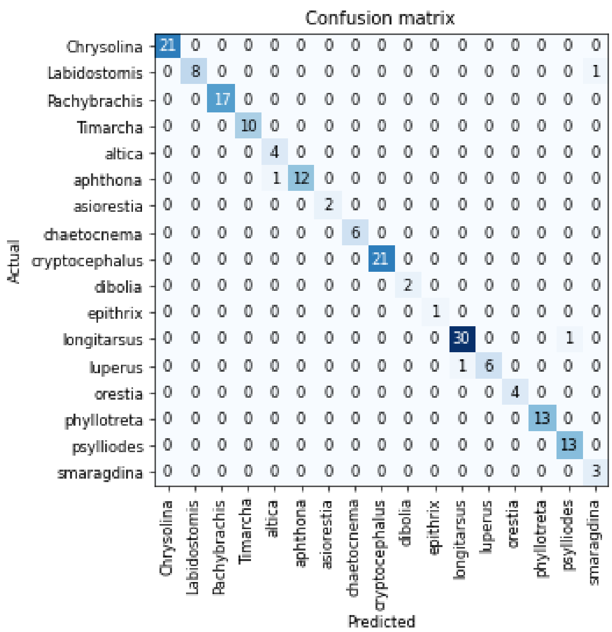

Figure4. Confusion matrix of ResNet-152

4. Discussion

Image-based identification of insects will be important for agriculture, forestry, ecology, and biodiversity [4]. Most of the studies conducted on image-based identification of insects, especially pests, performed with trap and field images [16]. On the other hand, image-based identification of insects in the collections is also valuable because information on species names and distributions is essential for scientific studies and environmental monitoring programs [39]. To the best of our knowledge, this is the first study that uses CNN's to identify leaf beetle genera. The present study showed that CNN's can accurately (>94% for studied all models) identify European leaf beetle genera from habitus images. The identification success in question is high because the images in the data set do not have noise that can affect learning such as color, resolution, brightness, clarity, and another object in an image. Although the identification success is high, the most important factors preventing higher success are the presence of a small number of images both in total (888) and for some genera such as *Epitrix*, *Orestia*, *Dibolia*, etc. When the results of this study are compared with other studies on collection-based images of insects, the following is seen. CNN identifies the 57 ant (Hymenoptera Order) genera from dorsal view (more than 43.648 images) with accuracy of 59.0% [39]. CNN could classify to genus level with 74.9% accuracy based on dorsal view images of 65.841 museum specimens belonging to 80 genera of the family Carabidae (Coleoptera Order) [40]. The pre-trained CNN could identify with 80–90% accuracy based on the dorsal habitus images of the family Miridae (Hemiptera Order) species [41]. It is not possible to compare the present study with the study on Hemiptera [41] because it tried to identify species-level. The present study showed that the dorsal habitus images during automated taxonomic identification by using CNN are more useful diagnostic tools for Coleoptera (both Carabidae [40] and Chrysomelidae) than Hymenoptera.

It is clear that more successful results were obtained in this study compared to the above-mentioned studies. Success differences among the mentioned studies may be caused by the differences in the image quality, network structure of the CNN, or the number of classes. However, one of the reasons for the higher success in this study may be the elimination of sex-induced bias by using only male individual images because leaf beetles show sexual dimorphism. Also, the position of the legs of ants (Hymenoptera) in habitus images might add more noise to the image than Carabidae and Chrysomelidae. On the other hand, in the context of network structure of the CNNs, the reason for the results of the present study is the architecture of the CNNs. The architecture of the VGG models causes vanishing gradient problems and degraded accuracy, although the architecture of the ResNet and DenseNet models solves vanishing gradient problems and further improves the accuracy of the model [42].

There have been significant developments in image classification methods in the last decade [43]. It is clear that we could expect more important improvements in the near future. On the other hand, there are some challenges to be overcome. One of them is that there aren't enough datasets to be used to train the deep learning algorithms. The other important challenges in terms of image classification are taking images of species, which will be used in the dataset, and validating the identification of these species. Although there are important efforts to digitize specimens stored in some natural history museums, the current efforts are not sufficient [44]. Thus, taxonomists, who are quite crucial to these developments, have an important task to contribute the image digitization. In conclusion, if the number of images increases and these images will be uploaded to a web-based imaging infrastructure, non-experts (farmers and foresters) and ordinary citizens will also be able to identify insects more easily than their images by using CNNs in the near future.

References

[1] T.C. Narendran, "An Introduction to Taxonomy". Zool. Surv. India, Kolkata, 2006.

[2] M. Ohl, "Principles of Taxonomy and Classification: Current Procedures for Naming and Classifying Organisms" in Handbook of Paleoanthropology, W. Henke, I. Tattersall, Eds. Berlin, Heidelberg, Springer, 2015, pp. 213-236.

[3] R. Sluys, "The unappreciated, fundamentally analytical nature of taxonomy and the implications for the inventory of biodiversity", Biodivers. Conservation, 22: 1095-1105, 2013.

[4] K.D. Prathapan, P.D. Rajan, "Advancing taxonomy in the global south and completing the grand Linnaean enterprise" Megataxa, 1(1): 73-77, 2020.

[5] P.A. Hutchings, "Major issues facing taxonomy-a personal perspective", Megataxa, 1(1), 46-48, 2020.

[6] X. Cheng, YH. Zhang, YZ. Wu, Y. Yue, "Agricultural Pests Tracking and Identification in Video Surveillance Based on Deep Learning" in Intelligent Computing Methodologies, D.S. Huang, A. Hussain, K. Han, M. Gromiha Eds. Lecture Notes in Computer Science, vol 10363. Springer, Cham, 2017, pp. 58-70.

[7] G. Figueroa-Mata, E. Mata-Montero, J.C. Valverde-Otárola, D. Arias-Aguilar, "Automated image-based identification of forest species: challenges and opportunities for 21st century xylotheques" in IEEE International Work Conference on Bioinspired Intelligence (IWOBI), Alajuela Province, Costa Rica, 2018, pp. 1-8.

[8] T. Kasinathan, D. Singaraju, S.R. Uyyala, "Insect classification and detection in field crops using modern machine learning techniques" in Information Processing in Agriculture, 2020.

[9] D.L. Saccaggi, K. Krüger, G. Pietersen, "A multiplex PCR assay for the simultaneous identification of three mealybug species (Hemiptera: Pseudococcidae)", Bull. Entomol. Res., 98: 27-33, 2008.

[10] J. Blair, M.D. Weiser, M. Kaspari, M. Miller, C. Siler, K.E. Marshall, "Robust and simplified machine learning identification of pitfall trap-collected ground beetles at the continental scale", Ecol. Evol., 10(23): 13143-13153, 2020.

[11] P.D. Hebert, A. Cywinska, S.L. Ball, J.R. Dewaard, "Biological identifications through DNA barcodes" Proc. R. Soc. London, Ser. B: Biological Sciences, 270(1512), 313-321, 2003.

[12] D. Dunbar, C. Nielsen, "Development of a DNA Bar-coding Project as a Biology Laboratory Module" J. Microbiol. Biol. Educ., 11(2): 160-161, 2010.

[13] C.O. Coleman, A.E. Radulovici, "Challenges for the future of taxonomy: talents, databases and knowledge growth" Megataxa, 1(1): 28-34, 2020.

[14] M. Vences, "The promise of next-generation taxonomy", Megataxa, 1(1), 35-38, 2020.

[15] J. Wäldchen, P. Mäder, "Machine learning for image based species identification", Methods Ecol. Evol., 9(11), 2216-2225, 2018.

[16] J.G.A. Barbedo, "Detecting and Classifying Pests in Crops Using Proximal Images and Machine Learning: A Review", AI, 1(2): 312-328, 2020.

[17] M. Tokmak, A. Kıraç, "Evrişimsel Sinir Ağları ile Örümcek Kuşugillerin Bazı Türlerinin Sınıflandırılması" Bilge International Journal of Science and Technology Research, 5 (1): 72-79, 2021.

[18] D. Grimaldi, M.S. Engel, "Evolution of the insects", Cambridge University Press, New York, USA, 2005, pp. 772.

[19] S.N. Yaakob, L. Jain, "An insect classification analysis based on shape features using quality threshold ARTMAP and moment invariant", Appl. Intell., 37(1), 12-30, 2012.

[20] P. Jolivet, K.K. Verma, "Biology of leaf beetles" Intercept Publishers, UK, 2002, pp. 332.

[21] N. Mirzoeva, "A study of the ecofaunal complexes of the leaf-eating beetles (Coleoptera, Chrysomelidae) in Azerbaijan" Turk. J. Zool., 25: 41-52, 2001.

[22] G. Magoga, D. Coral Sahin, D. Fontaneto, M. Montagna, "Barcoding of Chrysomelidae of Euro-Mediterranean area: efficiency and problematic species", Sci. Rep. 8(1): 1-9, 2018.

[23] D. Coral Sahin, G. Magoga, H. Özdikmen, M. Montagna, "DNA Barcoding as useful tool to identify crop pest flea beetles of Turkey" J. Appl. Entomol., 143(1-2): 105-117, 2019.

[24] www.cassidae.uni.wroc.pl/European%20Chrysomelidae/list%20of%20subfamilies.htm

[25] M. Hussain, J.J. Bird, D.R. Faria, "A Study on CNN Transfer Learning for Image Classification. Advances in Computational Intelligence Systems", in Advances in Intelligent Systems and Computing, vol 840, A. Lotfi, H. Bouchachia, A. Gegov, C. Langensiepen, M. McGinnity Eds. Springer, Cham., 2019, pp.191-202.

[26] K. O'Shea, R. Nash, "An introduction to convolutional neural networks". arXiv preprint arXiv:1511.08458, 2015.

[27] X. Bai, B. Shi, C. Zhang, X. Cai, L. Qi, "Text/non-text image classification in the wild with convolutional neural networks" Pattern Recognit., 66: 437-446, 2017.

[28] D. Scherer, A. Müller, S. Behnke, "Evaluation of Pooling Operations in Convolutional Architectures for Object Recognition" in Artificial Neural Networks – ICANN 2010, Lecture Notes in Computer Science, vol 6354, K. Diamantaras, W. Duch, L.S. Iliadis Eds. Berlin, Heidelberg, Springer, 2010, pp. 92-101.

[29] R. Yamashita, M. Nishio, R.K.G. Do, K. Togashi "Convolutional neural networks: an overview and application in radiology" Insights into Imaging, 9(4): 611-629, 2018.

[30] A. Gebrehiwot, L. Hashemi-Beni, G. Thompson, P. Kordjamshidi, T.E Langan, "Deep Convolutional Neural Network for Flood Extent Mapping Using Unmanned Aerial Vehicles Data" Sensors (Basel), 19: 1486, 2019.

[31] M. Togacar, B. Ergen, M.E. Sertkaya, "Subclass Separation of White Blood Cell Images Using Convolutional Neural Network Models" Elektronika ir Elektrotechnika, 25(5), 63-68, 2019.

[32] K. Simonyan, A. Zisserman, "Very deep convolutional Networks for large-scale image recognition" arXivPrepr arXiv14091556, 2014.

[33] K. He, X. Zhang, S. Ren, J. Sun, "Deep residual learning for image recognition" in Proc. IEEE Conf. Comp. Vis. Patt. Recogn., Las Vegas, USA, 2016, pp. 770–778.

[34] G. Huang, Z. Liu, L. Van Der Maaten, K.Q. Weinberger, "Densely connected convolutional Networks" in Proc. IEEE Conf. Comp. Vis. Patt. Recogn., Honolulu, Hawaii, 2017, 4700-4708.

[35] A.G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, H. Adam, "Mobilenets: Efficient convolutional neural networks for mobile vision applications", arXivpreprint arXiv:1704.04861, 2017.

[36] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, L.C. Chen, "Mobilenetv2: Inverted residuals and linear bottlenecks" in Proceedings of the IEEE conference on computer vision and pattern recognition 2018, pp. 4510-4520.

[37] Colab. (2021). Google Colaboratory. https://colab.research.google.com/

[38] fast.ai. (2021). fast.ai. https://www.fast.ai/

[39] A.C.R. Marques, M.M. Raimundo, E.M.B. Cavalheiro, L.F.P. Salles, C. Lyra, F.J. von Zuben, "Ant genera identification using an ensemble of convolutional neural networks" Plos one, 13(1), e0192011, 2018.

[40] O.L. Hansen, J.C. Svenning, K. Olsen, S. Dupont, B.H. Garner, A. Iosifidis, B.W. Price, T.T. Høye, "Species-level image classification with convolutional neural network enables insect identification from habitus images" Ecol. Evol., 10(2), 737-747, 2020.

[41] A. Knyshov, S. Hoang, C. Weirauch, "Pretrained Convolutional Neural Networks Perform Well in a Challenging Test Case: Identification of Plant Bugs (Hemiptera: Miridae) Using a Small Number of Training Images", Insect Syst. Diversity, 5(2), 3, 2021.

[42] H. Theivaprakasham" Identification of Indian butterflies using Deep Convolutional Neural Network" J. Asia-Pac. Entomol., 24(1), 329-340, 2021.

[43] T.T. Høye, J. Ärje, K. Bjerge, O.L.P. Hansen, A. Iosifidis, F. Leese, H.M.R. Mann, K. Meissner, C. Melvad, J. Raitoharju, "Deep learning and computer vision will transform entomology", PNAS, 118(2), e2002545117, 2021.

[44] B.P. Hedrick, J.M. Heberling, E.K. Meineke, K.G. Turner, C.J. Grassa, D.S. Park, J. Kennedy, J.A. Clarke, J.A. Cook, D.C. Blackburn, S.V. Edwards, C.C. Davis, "Digitization and the Future of Natural History Collections", BioScience, 70(3): 243-251, 2020.