
Image Processing Techniques and Neuro-computing Algorithms in Computer Vision

Ibrahim Goni, Asabe Sandra Ahmadu, Yusuf Musa Malgwi

Department of Computer Science, Faculty of Physical Science, Modibbo Adama University, Yola, Nigeria

Email address:

algonis1414@gmail.com (I. Goni)

To cite this article:

Ibrahim Goni, Asabe Sandra Ahmadu, Yusuf Musa Malgwi. Image Processing Techniques and Neuro-computing Algorithms in Computer Vision. *Advances in Networks*. Vol. 9, No. 2, 2021, pp. 33-38. doi: 10.11648/j.net.20210902.12

Received: July 30, 2021; **Accepted:** August 16, 2021; **Published:** October 12, 2021

Abstract: Computer vision is a multidisciplinary field that cannot be separated with image processing techniques and Neuro-Computing specifically Deep Learning (DL) algorithms, in recent time DL techniques enable computer vision to understand the content of an image, moreover, it is working hand in hand with image processing techniques because image preprocessing are essential components in digital image analysis. Therefore, the remarkable advancement recorded by computer vision today such as in remote sensing, security, medical imaging and robotics etc. The aim of this research work was to explore the technical and theoretical contributions of image processing techniques and DL algorithms to computer vision. A systematic method of literature review was adapted. Basic image processing techniques such as standardization, denoising, filtering, and segmentation are clearly explored, concept of DL algorithms are briefly discussed, recent reviewed articles (from 2018 to date) are obtained from top journals in computer vision thus; IEEE, Elsevier and ISPR and tabulated as a major source of information for this work. We have shown some of the software's used for the implementation of deep learning researches in computer vision. Finally we concludes and give recommendations based on our findings.

Keywords: Computer Vision, Deep Learning, Object Detection, Neuro-computing, Image Processing, Filtering

1. Introduction

Neuro-Computing techniques has achieved unprecedented progress in many areas of computer vision specifically Deep Learning (DL) ranging from object detection [1-10] images classification [11-17] image segmentation [18-20, 22, 23] and scene classification [24-30]. Moreover, in recent time the same techniques are also applied in remote sensing [31, 32], and [33]. It is noted in this work that most of the recent works in computer vision prefer to use the standard datasets for their analysis as in [34-36]. Despite the implementation of various DL techniques in the areas of computer vision many reviews and survey are also devoted to the exploration of DL algorithms in computer vision and are clearly discussed in the next section of this paper. The aim of this research work was to explore the recent contribution of image processing and Neuro-computing techniques in computer vision.

We have reviewed recent research articles and peer review papers from the top ranked journals of computer vision in the world such as ISPR Journal of photogrammetry and remote

sensing, IEEE Geoscience and remote sensing magazine ETC. This is to indicate the quality of this review and its uniqueness. We have downloaded 120 research articles and 60 review and survey papers. Due to the nature of our survey we have extract 77 papers that are related to our work and discarded the rest.

The rest of this work is organized in sections, Section 2 we have discuss the concept of Image Processing techniques in relation to computer vision, Section 3 we have discuss the concept of convolutional neural network as a major technique for object detection in satellite images. Section 4 we have discussed and reviewed the application of deep learning techniques in computer vision. Section 5 we have reviewed recent survey researches that applied deep learning techniques in computer vision. Section 6 we have identify some of the software's available for the implementation of computer vision researches and finally we have concluded and recommend.

2. Image Processing Techniques

An image can be expressed as two-dimensional function $f(x, y)$ where x and y represent the spatial coordinates and the altitude of f at any pair of coordinates (x, y) is known as the intensity or gray level of the image at that point. If x, y and the altitude values of f are all finite and discrete quantities the image is called digital image. The term gray level is used to describe the intensity of monochrome images. However colored image are formed by three colors Red, Green, and Blue (RGB). Digital images are mostly represented and store in a matrix form or in an array of numbers every digit in the matrix is located at a specific row and column every digit is used to represent a pixel in a two-dimensional picture element that is non-divisible element of digital image [37].

2.1. Image Standardization

One most important constraint that exists in some deep learning techniques, such as Convolutional Neural Network (CNN), is the need to resize the images in a dataset to a unified dimension. This implies that our satellite images must be cropped, resize and scaled to have identical widths and heights before fed to the learning algorithm for easy computation and avoid unnecessary errors. Especially the number of pixels values of the images must be the same.

2.2. Image Digitization

Generally images are converted into digital in two ways digitalization of the coordinate value or digitalization of the amplitude value, hence digital image are represented by $M \times N$ matrix.

2.3. Image Denoising

Image denoising is an important component in an image preprocessing because noise in digital images are inevitable in computer vision to preprocessed images they need to be denoised by using filters these includes;

1. Gaussian noise filters.
2. Mean filters of random noise removal.
3. Midpoint filter is seen to be a hybrid filter that combine statistical filter and averaging filter and which is good for denoising Gaussian noise and uniform noise.
4. Alpha-trimmed Mean Filter.
5. Contraharmonic filter.

2.4. Image Restoration

Image restoration is the method of regaining the natural characteristic of the image that has been degraded. We already define the real image as $f(x, y)$ and the degraded image as $g(x, y)$ the connected relationship between f to g is called degradation model represented as

$$g(x, y) = H[f](x, y) + n(x, y) \quad (1)$$

Where H is the degradation operator and n is the noise.

2.5. Image Segmentation

Segmented image is a processed image without noise and sometime sharp which can be an input f and the output could be an image g or not even an image but would be an attribute set of point representing the edges of f boundaries of object but, segmentation is based on certain criteria such as similarity, color texture or region of interest or any set of predefined rules.

If we consider a differentiable function $(x, y) \rightarrow f(x, y)$ in two dimensions to let defined its gradient operator as being the vector of first order partial derivatives.

$$\Delta f(x, y) = \left(\frac{\partial f}{\partial x}(x, y), \frac{\partial f}{\partial y}(x, y) \right) \quad (2)$$

And the gradient magnitude as Euclidean norm of the vector Δf

$$|\Delta f|(x, y) = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2} \quad (3)$$

3. Convolution Neural Network (CNN)

Deep learning is a subset of Neuro-computing, CNN is also a subset of DL technique that are suitable for computer vision research. It consists of input layer and many of feature detection layer which perform convolution, pooling and Rectified linear Unit, at convolutional stage it applies convolutional filters to activate certain features in the image, at the pooling stage it reduces the number of pixels in the image by using non-linear down sampling or sub-sampling. The second to the last layer is called classification layer, it converts 2D feature map to 1D feature map vector, it is fully connected with N -dimension output where N is the number of objects to be classified and the final output will show the probability that the input image belongs to the class of object under review. The architecture of CNN utilizes three major techniques local receptive fields, tied weights and spatial sub-sampling [38].

3.1. Unsupervised Learning

Deep unsupervised learning these categories of deep learning require no label data for training it learned from the significant features of the data and relationships in the data but the major disadvantage of this technique is the inability to provide accurate concerning data sorting as well as the computational complexity of the dataset. Several techniques are available in these categories; Deep Boltzmann Machine (DBM) and auto encoder which are widely applied in clustering. Deep Boltzmann machine all the connections in this technique are undirected with multiple hidden layers it applies stochastic maximum likelihood during the training process and requires no labels in the training dataset. The advantage of this technique is the ability to optimize the parameters of all layers. Deep belief network in this technique two top layers form an undirected graph and the lower layer forms a directed generative model [39].

3.2. Semi-Supervised Learning

Deep semi-supervised learning require semi-labeled dataset for training. They are widely applied for text document classification. This includes; generative adversarial network (GAN) the disadvantage of this technique is that unwanted features are learned from the input data and make wrong decision.

4. Deep Learning Applied in Computer Vision

The taxonomy of computer vision includes; object detection, image segmentation, scene classification, image retrieval, pattern recognition, target recognition and so on. In this section we have reviewed recent articles (from 2017 to date) that applied any of the DL techniques in computer vision.

Table 1. Deep Learning Algorithms in Computer vision.

Authors	Date	Network	Focus
1. Arshitha and Biju [39]	2020	CNN	Detection in satellite image
2. Scott <i>et al.</i> , [15]	2017	CNN	Land cover classification
3. Kadhim and Mohammed [40]	2020	CNN	Satellite image classification
4. Imamoglu <i>et al.</i> [41]	2018	CNN	Multi-spectral image classification
5. Deepthi, Sandeep and Suresh [42]	2021	CNN	Object detection in remote sensing
6. Deng <i>et al.</i> , [43]	2017	CNN	Object Recognition
7. Gao <i>et al.</i> [44]	2017	DCNN	Scene classification
8. Cheng, <i>et al.</i> [45]	2018	CNN	Scene classification
9. Boulleg and Farah [30]	2018	CNN	Image retrieval
10. Zhou, Newsam, Li and Shao [46]	2017	CNN	Object detection
11. Ye <i>et al.</i> [4]	2018	CNN	Land cover classification
12. Zhou, Deng and Shao, [48]	2018	RCNN	Urban land used classification
13. Zhang <i>et al.</i> , [47]	2020	OCNN	Image classification and segmentation
14. Zhang <i>et al.</i> , [48]	2018	CNN	Road extraction and building
15. Yu <i>et al.</i> [49]	2017	DCNN	Image classification
16. Mahdianpari <i>et al.</i> , [50]	2018	CNN	Classification of land cover
17. Alshehhi <i>et al.</i> [51]	2017	DL	Land used classification
18. Kussul <i>et al.</i> , [52]	2017	CNN	Semantic labelling of images
19. Volpi and Tuia, [53]	2017	RCNN	Oil and tank detector
20. Rene, He, Girshick and Sun [54]	2017	CNN	Detection of seal in satellite images
21. Muhammad <i>et al.</i> , [55]	2018	DL	Object detection in aerial images
22. Geng, wang, Fan, and Ma [56]	2017	MLE	Object Classification
23. Qin, Guo and sun, [57]	2017	DBN	Target recognition
24. Li, wu, and Du [58]	2017	DRNN	Image classification
25. Mou, Ghamisi and Zhu [59]	2017	DL	Image classification
26. Santara <i>et al</i> [60]	2017	DSL	Image classification
27. Chen, lin, Zhao, Wang, and Gu [12]	2017	DL	Object detection

Table 2. Survey Researches.

Author	Year	Network	Focus	Limitation
1. Ball, Anderson and Chan., [61]	2019	Deep learning	Comprehensive survey	No Image Pre-processing
2. Song, Gao, Zhu And Ma [62]	2019	CNN	Survey	No Image Pre-processing
3. Hyedari and Mountrakis [63]	2019	DNN	Meta-analysis	No Image Pre-processing
4. Zhang, Zhang And Du [64]	2020	Deep learning	Technical tutorial	No Image Pre-processing
5. Lu, Sun, and Zhang [65]	2019	CNN	Feature aggregation	No Image Pre-processing
6. Paoletti, Haut and Plaz [66]	2019	Deep learning	Review	No Image Pre-processing
7. Parikh, Patel and Patel, [67]	2020	Deep learning	Review	No image Pre-processing
8. Li <i>et al.</i> , [68]	2019	Deep learning	Overview	No Image Pre-processing
9. Pashae, Kamangir, Starck And Tissot,[69]	2020	Deep learning	Review	No Image Pre-processing
10. Liu <i>et al.</i> , [70]	2018	Deep learning	Advances and Feature	No Image Pre-processing
11. Laith <i>et al.</i> , [71]	2018	DL	Survey	No Image Pre-processing
12. Xiangwei, Doyen and Steven [72]	2019	DL	Recent advances	No Image Pre-processing
13. Lincheng <i>et al.</i> , [73]	2019	DL	Survey	No Image Pre-processing
14. Payal <i>et al.</i> , [74]	2020	DL	Survey	No Image Pre-processing
15. Jiao <i>et al.</i> [75]	2019	DL	Survey	No Image Pre-processing
16. Abhishek <i>et al.</i> [3]	2021	DL	Survey	No Image Pre-processing
17. Vipul and Roohie, [76]	2020	DL	Review	No Image Pre-processing

5. Recent Survey Articles

In this section we have centered our search to recent survey articles (from 2018 to date) that applied deep learning

techniques in computer vision in addition to see limitations and build on that however, it comes to our noticed that all reviews are subjected to deep learning only not dwelling into the aspect of image processing which is an important part in computer vision because image preprocessing is one of the

building blocks of datasets for computer vision. Table 2 summarized the recent survey articles.

6. Image Processing and Deep Learning Software

Image Preprocessing softwares for deep learning algorithms are available for the implementation of computer vision research but the common ones are MatconvNet (MATLAB), Tensorflow (C++ and python), R, Caffe (C++), Torch (C and Lua), Keras (python), Deeplearning4j (Java), MxNet, Theano (Python), Gluon (C++), OpeenDeep (Python), NTK (C++) and ConvnetJs. Some of these softwares are open source and some are not [77].

7. Conclusion

In this work we conducted a thorough review in the application of deep learning techniques in computer vision. We have subjected our search towards various categories of deep learning algorithms together with their associated architectures that are applied in computer vision researches, we have used systematic format of literature review and explored critically the state-of-the-art in all aspects of computer vision and also explored survey and review researches in the state-of-the-art. Furthermore, we have summarized the major softwares and toolboxes used for the implementation of computer vision researches.

8. Recommendations

Based on the findings of this review work the following recommendations have been made;

1. Several issues in the area of DL in relation to image processing are still on silent mode they need to be explored.
2. There is need to explore more on datasets issues in regard to DL.

References

- [1] Sevo L. and Avramovic, (2016). A Convolutional Neural Networks Based Automatic object Detection on Aerial images. *IEEE Geoscience. Remote Sensing letter* 2016 13, 740-74.
- [2] Jiao L., F. Zhang, F. Liu, S. Yang, L. Li, Z. Feng, R. Qu, (2019). A survey of deep learning- based object detection, arXiv: 1907.09408.
- [3] Abhishek G., Alagan A., Ling G., Ahmed S. K. (2021). Deep learning for object detection and Scene perception in self-driving cars: Survey, challenges, and open issues. *Science Direct Array* 10 (2021) 100057.
- [4] Cheng, P. Zhou, and J Han, "learning rotation-invariant convolution neural networks for object detection in VHR optical remote sensing images, *IEEE Trans. Geoscience and Remote Sensing*, 54 (12), 7405-7415, 2016.
- [5] Sevo and A. Avramovic, (2016). Convolutional Neural Network based automatic object detection on arial images *IEEE Geoscience and remote sensing letter*. vol. 13, no. 5, pp. 740-744, 2016.
- [6] Girshick, J. Donahue, T. Darrell, and J. Malik, (2016) Region-based convolutional networks for Accurate object detection and semantic segmentation, "*IEEE Trans. Pattern Anal. mach. Intell.* vol. 38, no. 1, pp 142-158, 2016.
- [7] Ross G., Jeff D., Trevor D., Jitendra M., (2014). Rich feature hierarchies for accurate object detection and semantic segmentation, *In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2014, pp. 580-587.
- [8] Joseph R., Santosh D., Ross G., Ali F., (2016) You only look once: Unified, real-time object detection, *In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 779-788.
- [9] Lin T. Y., Dollár P., Girshick R., K. He, B. Hariharan, and S. Belongie, (2017). Feature pyramid networks for object detection. *In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2117-2125, 2017.
- [10] Singh S. and L. S. Davis, (2018). An analysis of scale invariance in object detection snip," *in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 3578-3587.
- [11] Romero, Gatta, Camps-valls, (2016). Unsupervised deep feature extraction for remote sensing image classification. *IEEE Transaction of Geoscience and Remote sensing* 54 (3), 1349-1362.
- [12] Chen, Y., Lin Z., Zhao X., Wang G., Gu Y. (2014). Deep learning-based classification of hyper spectral data. *IEEE J. sel. Top. Appl. Earth Obs. Remote Sensing*. 7 (6), 2094-2107.
- [13] Marmanis D., Datcu M., Esch T. and Stilla U., (2016). Deep learning earth observation classification using ImageNet pre-trained networks. *IEEE Geoscience and remote sensing letter* 13 (1). 105-109.
- [14] Kussual, N., Lavreniuk, M., Shelestov S. (2017). A deep learning classification of land cover and crop types using remote sensing data. *IEEE Geoscience Remote sensing Letter*. 14, 778-782.
- [15] Scott G., M. England, W. Starns R. Marcum, and C. Davis, (2017). Training deep Convolution neural networks for land-cover classification of high-resolution Imagery", *IEEE geosciences and Remote sensing letters*, Vol. 14, no. 4, 2017.
- [16] Goodin, D. g., Anibas, k. L., Bezymennyi, M. (2015). Mapping land cover and land use from object-based classification: an example from a complex agricultural Landscape. *Transaction of Geosciences and Remote Sensing*. 63, 382-396.
- [17] Long, E. Shelhamer, and T. Darrell, (2015). Fully convolutional networks for semantic Segmentation, *in proceeding. IEEE International. Conf. computer vision and pattern recognition (CVPR)*, 3431-3440.
- [18] H. Noh, S. Hong and B. Han, (2015) Learning de-convolutional network for semantic segmentation, *In Proceeding IEEE international conference and computer vision (ICCV)*, 2015, pp. 1520-1528.

- [19] Zhao J., Feng J., Wu X. and Yan S. (2017). A Survey on deep learning-based fine-grained Object classification and semantic segmentation. *International Journal of Automat. Comput.* 14 (2), 119-135.
- [20] Duan, F. Liu, L., Jiao, P. Zhao, and L., Zhang, (2017). SAR image segmentation based on convolutional- wavelet neural network and Markov random field, *Pattern Recognition*, 64, 255-267.
- [21] Kampffmeyer, A. B. Salberg, and R. Jenssen, (2016) semantic segmentation of small objects and Modeling of uncertainty in urban remote sensing image using images using deep convolutional neural networks," in *Proceeding IEEE int. conf. computer vision and pattern recognition (CVPR) workshop*, 1-9.
- [22] Cheng G. and Han J. (2016). A survey on object detection in optical remote sensing images. *ISPRS Journal of Photogrammetry and Remote sensing*. 117, 11-28.
- [23] Hu, G. S. Xia, Z. Wang, X. Huang, L. Zhang, and H. Sun, (2015). Unsupervised features learning via spectral clustering of multidimensional patches for remotely sensed scene classification, *IEEE Journal select. Topics appl. Earth observed Remote Sensing*, 8 (5) 203.
- [24] Zou, L. Ni, T. Zhang, and Q. Wang, (2015) Deep learning based feature selected for remote sensing scene classification, *IEEE Geoscience remote sensing letter*. 12 (11). 2321-2325, 2015.
- [25] Hu, G-S. Xia, J. Hu, and L. Zhang, (2015). Transferring deep convolutional neural networks for the scene classification of high-resolution remote sensing imagery, *Remote Sensing*, 7 (11) 14680-14707.
- [26] Zhang, B. Du, and L. Zhang, (2015). Scene classification via a gradient boosting random convolutional network framework, *IEEE Transaction Geoscience and Remote sensing*. 54 (3), 1793-1802.
- [27] Cheng, G.; Ceyuan, Y.; Xiwen, Y.; Guo, L.; Junwei, H. (2018). When deep learning meets Metric learning: remote sensing image scene classification via learning discriminative CNNs. *IEEE Transaction Geoscience Remote Sensing*. 56, 2811–2821.
- [28] Cheng, G., Ma, C., Zhou, P., Yao, X., Han, J. (2016). Scene classification of high resolution remote sensing images using convolutional neural networks. In *Proceedings of the 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, Beijing, China, 10–15 July, 2016, 767–770.
- [29] Boualleg, Y., Farah, M. (2018). Enhanced interactive remote sensing image retrieval with scene Classification convolutional neural networks model. In *Proceedings of the IGARSS 2018—2018 IEEE International Geoscience and Remote Sensing Symposium*, Valencia, Spain, 22–27 July 2018. 4748–4751.
- [30] Ye, F.; Xiao, H.; Zhao, X.; Dong, M.; Luo, W.; Min, W. (2018). Remote Sensing Image Retrieval Using Convolutional Neural Network Features and Weighted Distance. *IEEE Geoscience Remote Sensing Letter* 15, 1535–1539.
- [31] Zhou, W.; Newsam, S.; Li, C.; Shao, Z. (2017). Learning Low Dimensional Convolutional Neural networks for high-resolution remote sensing image retrieval. *Remote Sensing*, 9, 489.
- [32] Li, W., Fu, H., Le, Y., Peng, G., Feng, D., Li, C., Clinton, N. (2016). Stacked auto encoder based deep learning for remote-sensing image classification: a case study of African land-cover mapping. *International Journal of Remote Sensing*. 37, 5632–5646.
- [33] Zhong, B. Yang, G. Huang, F. Zhong and Z. Chen, (2016). Remote sensing image fusion with Convolution neural network, *sensing imaging*. 17 (1) 2016.
- [34] Xiao X. Z., Devis T., Linchao M., Gui-Song X., Liangpei Z., Feng X. and Frieddrich F. (2017). Deep learning in Remote Sensing: A Comprehensive Reviw and list of resources. *IEEE Geoscience and Remote Sensing Magazine* Doi 10.1109/MGRS.
- [35] Han, D. Zhangm G. Cheng, L. Guo, and J. Ren, (2015). Object Detection in Optical Remote sensing image based on weekly supervised learning and high-level feature learning," *IEEE Transaction Geoscience and remote sensing*, 53 (6), 3325-3337.
- [36] Milan, S., Vaclav H. and Roger B., (2015). *Image Processing, Analysis and Machine Vision* Cengage Learning 200 First Stamford Place, 4th Floor Stamford, CT 06902 USA.
- [37] Athanasios V., Kolas D., Anastasios D. and Eftychios P., (2018). Deep learning for computer vision: A brief review. *Hindawi Computational intelligence and Neuroscience*.
- [38] Srivastava N. and Salakhutdinov R., (2014). Multimodal learning with deep Boltzmann machines, *Journal of Machine Learning Research*. 15, 2949–2980.
- [39] Arshitha F. and Biju K. S. (2020). Accurate detection of building from satellite images using CNN. *IEEE*.
- [40] Kadhim, Mohammed and Abed, Mohammed, (2020). Convolution neural network for Satellite Image Classification.
- [41] Imamoglu, N., Martinez G., Pascual, hamaguchi, Ryuhei, Sakurada, Ken and Nakamura, R. (2018). Exploring recurrent and feedback CNNs for Multi-Spectral Satellite image classification *Proceeding in Computer Science*. 140, 162-169.
- [42] Deepthi, S., Sandeep K. and Suresh L. (2021). Detection and Classification of Objects in Satellite Images using Custom CNN. *International Journal of Engineering Research & Technology*. 10 (6), 629-635.
- [43] Ding, J., Chen B., Liu H., and Huang M., (2017). Convolutional neural network with data augmentation for SAR target recognition, *IEEE Geoscience and Remote Sensing Letter*, 13 (3), 364-368.
- [44] Gao, F., Huang, T., Wang, J., Sun, J., Hussain, A., Yang, E. (2017). Dual-branch deep convolution neural network for Polari metric SAR image classification. *Applied Science*. 7, 447.
- [45] Cheng, G. Ceyuan, Y. Xiwen, Y.; Guo, L. Junwei, H. (2018). When deep learning meets Metric learning: remote sensing image scene classification via learning discriminative CNNs. *IEEE Transaction Geoscience Remote Sensing*. 56, 2811–2821.
- [46] Zhou, W., Deng, X., Shao, Z. (2018). Region convolutional features for multi-label remote sensing image retrieval. arXiv arXiv: 180708634.

- [47] Zhang, C., Yue, P., Tapete, D., Shangguan, B., wang, M., Wu, Z. (2020). A multi-level context- Guided Classification method with object-based convolutional neural network for land Cover Classification using very high resolution remote sensing images. *International Journal of Application on Earth Observation and Geo-information*. 88, 102086.
- [48] Zhang, S., Wen, L., Bian, X., Lei, Z., and Li, S. Z. (2018). Single-shot refinement neural network for object detection. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 4203–4212.
- [49] Yu, H., Ma, Y., Wang, L., Zhai, Y., Wang, X. (2017). A landslide intelligent detection method based on CNN and RSG_R. *IEEE international conference on mechatronics and Automation (ICMA)*. 40-44 6-9.
- [50] Mahdianpari, M., Salehi, B., Rezaee, M., Mohammedimanesh, F., Zhang, Y. (2018). Very deep convolutional neural networks for complex land cover mapping using multi-spectral Remote sensing Imagery. *Remote sensing*. 10, 1119.
- [51] Alshehhi, R., Marpu, P. R., Woon, W. L., and Dalla M. M. (2017). Simultaneous extraction of roads and buildings in remote sensing imagery with convolutional neural networks. *ISPRS Journal of Photogrammetry and Remote Sensing*. 130, 139-149.
- [52] Kussul, S. S. (2017). Deep learning classification of land cover and crop types using remote sensing data. *IEEE Geoscience and Remote sensing letter*. 14 (5). 778-782.
- [53] Volpi, M. and Tuia, D. (2017). Dense Semantic Labeling of Sub-Decimeter Resolution Images with Convolutional Neural networks *IEEE Geoscience. Remote sensing letter*. 2017, 55, 881-893.
- [54] Ren, S., Kaiming H., Ross G., and Jian S. (2017). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks.” *IEEE transactions on pattern analysis and machine intelligence*, 39 (6): 1137–49.
- [55] Muhammad K., Ahmad J. and Baik S. W. (2018). Early fire detection using CNN during surveillance for effective disaster management. *Neurocomputing* 288 30-42.
- [56] Geng, H. Wang, J. Fan, and X. Ma, (2017). Deep supervised and contractive neural network for SAR image classification. *IEEE Transaction Geoscience Remote Sensing* 55 (4), 2442-2459, 2017.
- [57] Qin, J. Guo, and W. sun, (2017). Object-oriented ensemble classification for polarimetric SAR imagery using restricted Boltzmann machines, *Remote Sensing Letter*, 8 (3), 204-213, 2017.
- [58] Li W., Wu, G., and Du, Q. (2017). Transferred deep learning for anomaly detection in hyper Spectral imagery, *IEEE Geoscience and Remote sensing. Letter*. doi: 10.1109/LGRS.2657818.
- [59] Mou, L., P. G. and Zhu X. X. (2017). Deep recurrent neural networks for hyper spectral image classification. *IEEE Transactions on Geosciences and Remote Sensing*, 55 (7).
- [60] Santara, A., Mani, K., Hatwar, P., Singh, A., Garg, A., Padia, K., and Mitra, P., (2017). Bass net: Band- Adaptive spectral-spatial feature learning neural network for hyper spectral image classification. *IEEE Transaction of Geoscience and Remote Sensing*, 55 (9), 5293-5301.
- [61] Ball J. E., D. T. Anderson, and C. S Chan, (2019). Comprehensive Survey of Deep Learning on Remote Sensing Theories, tool and challenges for the community. *Journal of Applied Remote Sensing*. 11. (4). 42-56.
- [62] Song J., S. Gao, Y. Zhu, And C. Ma, (2019). A Survey of Remote Sensing Image classification Based on CNNs, *Big Earth Data*, 3 (3). 232-254.
- [63] Heydari S. S. and G. Mountrakis. (2019). Meta-analysis of deep-learning in remote sensing: a comprehensive study of mono-temporal classification to support vector machines. *ISPRS Journal of Photogrammetric and Remote Sensing*. 152, 192-210.
- [64] Zhang, L. Zhang, and B. Du, (2020). Deep Learning for Remote Sensing Data: A Technical Tutorial on the state of art, *IEEE geosciences and remote sensing magazine*, 4 (2). 22-40.
- [65] Lu X., Sun H. and Zheng, X. (2019). A feature aggregation convolutional neural network for remote sensing scene classification. *IEEE Transaction on Geosciences and Remote Sensing*. 57 (10). 78947906.
- [66] Paoletti, M., Haut J., Plaza J., and Plaza A. (2019). Deep Learning Classifier for Hyper-Spectral Imaging: a review. *ISPRS Journal of Photogrammetric and Remote Sensing*, 158, 279-317.
- [67] Parikh, H., S. Patel, and Patel, V. (2020). Classification of SAR And POLSAR Images Using Deep Learning: A review of international journal of image and data fusion, 1 (1), 1-32.
- [68] Li Y., Zhang H., Hue X., Jiang Y., and Shen Q. (2018). Deep learning for remote sensing image classification. *A survey, Wiley Interdisciplinary Review: Data mining and knowledge Discovery* 8 (6) 1264.
- [69] Pashae M., H. Kamagir, M. J. Strrek, and P. Tissot, (2020). Review and Evaluation of Deep Learning Architecture’s for efficient land cover mapping with UAS hyper-spatial Imagery: a case Study over a wetland, *Remote Sensing Image Classification*, 12 (6). 959.
- [70] Liu, Y., Chen X., Wang Z. J., Ward R. K and Wang X., (2018). Deep learning for pixel-level image fusion: Recent advances and future prospects. *Inf. Fusion* 42, 158-173.
- [71] Laith A., Jinglan Z., Amjad J. H., Ayad A. D., Ye D., Omran A. S., Santamaria J., Mohammed A. F., Muthana A. A. and Laith F., (2021). Review of Deep learning: Concepts, CNN architectures, Challenges, application and feature directions. *Journal of Big data Springer open*. 8 (53). 1-74.
- [72] Xiangwei W., Doyen S., and Steven, C. H. H. (2019). Recent advanced in deep learning for object detection GrXiv. 1908. 03673vi.
- [73] Lincheng J., Fan Z., Fan L., Shuyuan Y., Zhixi F. and Rang Q. (2019). A survey of deep learning-Based object detection. *IEEE Access Multidisciplinary*. 7, 128837-128867.
- [74] Payal M., Sharma A. and Singh R., (2020). Deep learning-based object detection in low-altitude UAV datasets: A survey, *Image and Vision computing* <https://doi.org/10.1016/j.imavis.2020.104046>.
- [75] Jiao and F. Liu, (2019) wishart deep stacking network for the fast polSAR image classification, “*IEEE Trans. Image process*, 25 (7). 3273-3286.
- [76] Vipul, S. and Roohie, N. M. (2020) A comprehensive and systematic look up into deep learning based detection techniques: A review. *Computer Science Review* 38 Elsevier. 1-29.
- [77] Jude D. H., and Vania V. E., (2017). Deep learning for image processing applications IOS Press Asterdam, Berlin and Washington DC.