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Deep Learning Applied in Computer Vision

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Abstract— Computer vision is a multidisciplinary field in computational intelligence and artificial intelligence that guide intelligent systems and machine towards understanding the content of images or video. It has come under the spotlight in recent time due to the remarkable advancement and breakthrough day-by-day such as autonomous driving, intelligent systems, pedestrian system, robotics, medical imaging, remote sensing, object detection, security, speech sequence, image registration, biometric technologies, image retrieval and video processing to mention just a few. The aim of this work is provide a systematic review in the application of deep learning in various aspect of computer vision that is object detection, object classification, scene classification, image segmentation, image retrieval, image registration, object recognition, feature extraction, image fusion and anomaly detection by providing detail description in a systematic way of all the deep learning techniques; Convolutional Neural Network (CNN), Deep Boltzmann Machine (DBM) and Deep Belief Network (DBN) that are applied in solving this problems of computer vision. This work also explored all the review and survey researches that applied deep learning techniques in computer vision in a systematic format and identify the countries that the researches was conducted which is one of the unique attribute of this paper that make it exceptional in a state-of-art review and surveys. In addition to datasets that used in the recent research of computer vision with the software and toolboxes used for the implementation of deep learning techniques in computer vision. We have also identified all the top journals (ISPRS Journal of Photogrammetry and Remote sensing, IEEE Geoscience and Remote Sensing Letter, IEE Transaction of Geoscience and Remote sensing etc.) and conferences proceedings (IEEE Conference of Computer vision and Pattern recognition) for advanced publication of computer vision researches in the world. This work would serve as a roadmap for the any researcher that want to use deep learning algorithms in computer vision.

Keywords— Computer vision, Deep learning, Convolutional Neural network, Deep Boltzman Machine, Deep Belief Network, object detection.

BACKGROUND

Deep Learning algorithms has achieved exponential progress and remarkable performances in computer vision. Sequel to it promising performances it is widely applied in several areas of computer vision these include; image classification object detection scene classification and land use and land cover Chen, Lin, Zhao, Wang, Gu (2014); Zou, Ni, Zhang, Wang, (2015); Chen, Zhao and Jia, (2015); Romero, Gatta, Camps,-valls, (2016); Cheng and Han, (2016); Marmanis, Datcu, Esch and Stilla, (2016); Yu *et al*., (2017); Kussul,

Volume: 01 / Issue: 01 / 2021 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

Skakum, Shelestov, (2017); Sharma, Liu, Yang and Shi, (2017); Vetrivel, Gerke, kerl, Nex and Vosselman, 2018). Specifically for image classification Krizhevsky, Sutskever, and Hinton, (2012); object detection Lin, Dollár, Girshick, He, Hariharan, and Belongie, (2017); Dai, Li, He, and Sun, (2016); Zhou, Ni, Geng, Hu, and Xu, (2018); Zhang, Wen, Bian, Lei, and Li, (2018); Singh and Davis, (2018). Motion detection, object positions, image segmentation, event tracking, pattern recognition and texture extraction Godfellow, Bengio and Courvile, (2013). Speech recognition, Zhang, Pezeshki, Brakel, Zhang, Bengio, and Courville, (2017). Moreover, recent reviews are also devoted in the application of deep learning to remote sensing Liu Y., Chen, Wang, Ward and Wang, (2018) but they have focused specifically for data fusion and left others areas. In addition to Zhu, Tuia, Mou, Xia, Zhang, Xu and Fraundorfer, (2017) focused on 3D modeling application but they ignore the very important aspect of remote sensing such as classification and object detection. But Lei, Yu, Xueliang, Yuanxin, Gaofei and Brian, (2019) conducted a thorough review on the application of deep learning in remote sensing with a clear analysis as well. We have reviewed many articles, survey researches and conferences in computer vision however, most of the scholars prefer to use standard datasets in training and testing the performance of their system as in (Xia *et al.*, 2017) Uc-Merced dataset also used in (Zhao and Duo, 2016) (Scott *et al*., 2017) while (Zhong *et al,* 2016) and (Han *et al*., 2017). Used WHU-RS dataset and also (Zou *et al*., 2015) and (Yang *et al*., 2017) used RSSCN7 dataset for their training and testing their models. In addition to some scholars had extend the training samples because of the nature of the dataset to enhance the performance of the system (Marmani *et al*., 2016) and (Scott *et al*., 2017).

This paper reviews the recent research articles and peer reviewed papers from top journals in computer vision. We have subjected our search to IEEE and Elsevier Journals with some few Q1 journals in the computer vision journals based on this search we have found (687) research articles and (120) reviews, survey, comprehensive survey, analysis and overview researches. All this articles are mostly found in (32) Journals including conference proceedings.

However, we have not utilized all the conference papers obtained because they do not have sound academic background so we have used very few. This reviewed is quite different from the previous reviews because we have explored extensively on both deep learning and computer vision techniques. We have shown the top journals in computer vision, we have also used systematic review format for easily understanding and identifying the gaps. We have also review the datasets used in computer vision researches and also the software for implementing computer vision researches.

The major difference between this reviews and previous reviews is that it covers all aspect of computer vision such as object detection, image classification, land cover, image segmentation, scene classification, image retrieval, target recognition, semantic segmentation, feature extraction, image fusion and anomaly detection to mention just a few which was not found in the previous reviews. In the previous reviews they focus on a specific computer vision technique thus; segmentation, classification object detection and so on.

Volume: 01 / Issue: 01 / 2021 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

Table 1: List of Abbreviation used in this research

Abbreviation	Full meaning
1. DL	Deep Learning Convolutional Neural
2. CNN	network
3. DBN	Deep Belief Network
4. DBM	Deep Boltzmann Machine
5. GAN	Generative Adversarial Network
6. AE	Auto-encoder
7. USL	Unsupervised Learning
8. NN	Neural Network
9. DSL	Deep Supervised learning
10. WSL	Weekly Supervised Learning
11. RGB	Red Green Blue

Deep learning algorithms

Deep learning is a family of computational methods and methodologies, techniques and models encompassing many categories of neural networks (CNN, RCNN, DNN) , hierachical probablistic models and a many unsupervised and unsupervised learning algorithm (Athanasioa et al., 2018) deep learning made unprescendented progress in computer vision such as image classsification segmentation, image retrival and scene classification. In the context of computer vision image classification or segmentation is the processing of classifying various objects in an image such as human being, mountains, water bodies, trees, forest, ship, car, and mineral resources etc. classsification and segmmentation are implemented using supervised, unsupervised and semisupervised learning algorithms. In all these algorithms used feature extraction is the major parameter used in image classification. As applied by researchers using CNN, SVM, PCA, K-means algorithm, minimun distance classifier and bayesian classifier in (Tui et al., 2015; Han et al., 2018; Srivastava et al., 2019; Cao et al., 2020; Rasti 2020; Noh et al., 2015; Hu and Koltun, 2015; Riese, Keller and Hinz, 2020). In this section we have explored several classification of deep learning techniques applied in computer vision such as CNN, DNN, RNN, DBM and GAN.

Deep learning classification

Deep learning algorithms has achieved unprecedented progress in different application domain ranging from security, bioinformatics, social media, remote sensing, digital forensic, medical imaging and computer vision. Categorically deep learning is classified into; deep supervised learning, deep unsupervised learning, semi-supervised learning and reinforcement learning. Deep supervised learning algorithms are trained with a label dataset. Data most content inputs and the resulting outputs. It is the simplest technique to implement among different categories of DL techniques because it has the ability to generate output from the prior knowledge learned. There are several techniques in supervised learning; CNN, DNN and RNN (Laith et al., 2021).

Volume: 01 / Issue: 01 / 2021 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

Convolutional neural network is a deep learning technique that consist of inputs 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 pixel in the image by using non-linear down sampling or sub-sampling. Moreover, pooling process does not affect the depth dimension of the image, average pooling and max pooling are the most widely used strategies in this unit (Boureu, Ponce and Lecun, 2010). Many other pooling layer are also explored in the recent literature; spatial pyramid (He, Zhang, Ren and Sun, 2015) and (He, Zhang, Ren and Sun, 2014). And def-pooling (Ouyuan et al., 2015) stochastic pooling in (Wu and Gu, 2015) and at the rectification linear unit it lets negative values to zero and maintain all the positive values. 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 belong to the class of object under review. The architecture of CNN utilizes three major techniques local reception fields, tied weights and spatial sub-sampling (Athanasios et al., 2018).

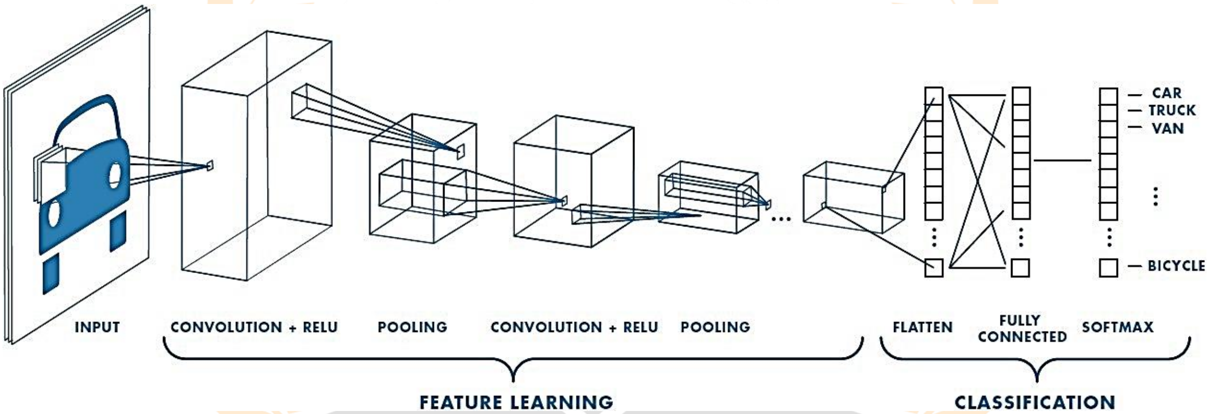

Fig. 2.1. CNN architecture (Sumita, 2018)

Deep unsupervised learning these category of deep learning requires no label data for training it learned from the significant feature of the data and relationship 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 this 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 require no label in the training dataset. The advantage of this technique is the ability to optimize the parameters of all layers (Srivastava and Salakhutdinov, 2014). Deep belief network in this technique two top layers form undirected graph and the lower layer form directed generative model. DBN are trained using greedy method as proposed in (Hinton and Salakhutdinov, 2006). Deep semi-supervised learning requires semi-labeled dataset for training. They are widely applied for text

Volume: 01 / Issue: 01 / 2021 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

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.

Deep learning in object detection

In this section we conducted a thorough survey on the application of deep learning in computer vision such as object detection in images, motion detection in videos and pattern recognition. An object detection is the process of detecting objects in a digital image such as human settlement, mountains, forest, cars, roads, etc. (Ouyandng, Zeng and Wang, 2017). The taxonomy of object detection includes; edge detection, salient object detection, pose detection, face detection highlight detection, fine grained visual detection, multi-domain object detection, point cloud 3D object detection, 2D 3D pose detection and pedestrian detection. Basically deep learning based object detection in computer vision is divided into two categories; one stage object detectors and two stage object detectors. In this categories many architectures are recently introduced and applied in object detection. One stage objectors are commonly applied in object detection by using region of interest. YOLO (you only look once) it was introduced in 2015 it normally cluster the input images into patches and locate the object in all the patches, SSD it was introduced in 2016 in order to overcome the major shortcomings identify in YOLO, RetinaNet which was introduced in 2017 by Tsing et al., (2017). Two stage object detectors; the most common architectures used under this category that are applied in object detection are R-CNN which was introduced by (Ross et al., 2014) however, it is time consuming in training and testing. SPP-net was introduced in 2014 and proposed by (Kaiming et al., 2015). Fast-CNN is an architecture that combine the future of R-CNN and SPP-net, Faster R-CNN was introduced by (Shaoqing et al., 2015) it uses a fully connected CNN called Region proposal network (RPN), R-FCN it was introduced in 2016 by Jifeng et al., (2016) its apply region based convolutional neural network and Mask R-CNN was introduced by (Kaiming et al., 2017).

Table 2: Deep Learning Algorithms in Computer vision

Authors and date	Techniques	Focus
Goodin, Anibas and Bezymennyi (2015)	CNN	Object based classification in
Wang, Song, Chen, Yang, (2015).	CNN	Road network extraction
Arshitha and Biju (2020).	CNN	Detection in satellite image
Scott *et al* ., (2017)	CNN	Land cover classification
Luus *et al* ., (2015)	CNN	Land used classification
Kadhim and mohammed (2020)	CNN	Satellite image classification
Imamoglu *et al.*, (2018).	CNN	Multi-spectralimage classification
Li, Zhang, Huang and Yuille (2018)	DRCNN	Deep network
Mou and Zhu (2017)	CNN	Geo-spatial object detection
Deepthi, Sandeep and Suresh (2021)	CNN	Hyper spectral image
Zhong *et al.*, (2016)	CNN	Classification of object in satellite
Deng *et al* ., (2017)	CNN	Building and road extraction
Liang and Xiaolin, (2015)	RCNN	Object detection in remote sensing

Volume: 01 / Issue: 01 / 2021 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

Liang and Hu, (2015)	RCNN	Object recognition
Gao *et al.,* (2017)	DCNN	Object Recognition
Li *et al.*, (2016)	DL	Image classification
Cheng, et al., (2016)	CNN	Image classification
Cheng, et al., (2018)	CNN	Scene classification
Zhang, Du and Zhang, (2016)	CNN	Scene classification
Boulleg and Farah, (2018)	CNN	Scene classification
Zhou, Newsam, Li and Shao (2017)	CNN	Scene classification
Ye et al., (2018)	CNN	Image retrieval
Zhou, Deng and Shao, (2018)	RCNN	Image retrieval
Cao, Ni and Dou, (2016)	OCNN	Object detection
Zhang et al., (2020)	OCNN	Land cover classification
Zhang et al., (2018)	CNN	Urban land used classification
Yu et al., (2017)	DCNN	Intelligent land slide detection
Mahdianpari et al., (2018)	CNN	Image classification and segmentation
Alshehhi et al., (2017)	DL	Road extraction and building
Bergado et al., (2016)	CNN	Image classification
Kussul et al., (2017)	CNN	Classification of land cover
Castellucio et al., (2015)	CNN	Land used classification
Sevo and Avramovic, (2016)	CNN	Object detection in aerial images
Volpi and Tuia, (2017)	RCNN	Semantic labeling of images
Rene, He, Girshick and Sun (2017)	CNN	Real time object detection
Muhammad et al., (2018)	DL	Early fire detection
Zhang, Shi and wu (2015)	DCNN	Oil and tank detector
Salberg, (2015)	NN	Detection of seal in satellite images
Sevo and avramoric, (2016)	SL	Object detection in aerial images
Zhang, Zhang and Xu (2016)	DNN	Aircraft detection
Tang *et al* (2015)	WSL	Ship detection
Han *et al.,* (2015)	DNN	Object detection
Zhang, Du, and Zhang (2016)	DCNN	Scene classification
Hu,Xia,Hu, and zhang (2015)	DL	Scene Classification
Yang, yin, and Xia (2015)	USL	Image classification
Hu et al (2015)	CNN	Spectral clustering
Cheng, Zhou, and Han (2016)	DL	Object detection
Zou, Ni, Zhan and Wang (2016)	DCA	Scene classification
Geng, fan , wang, ma, li, and chen (2015)	DSNN	Scene classification
Geng, wang, fan, and ma, (2017)	MLE	Image classification
Hou, Kou, and Jiao (2016	AE	Image classification
Zhang, Ma, and zhang, (2016)	BM	Image classification
Qin, Guo and sun, (2017)	DBN	Object Classification
Zhoa, Jiao, Gu, Zhao, (2017)	CNN	Image classification

Duan Liu, Jiao, Zhao, (2017)	CNN	Image segmentation
Ding, chen, Liu, and Huang, (2016)	DCNN	Target recognition
Chen *et al.*, (2016)	DL	Target recognition
Chen and wang (2014)	DL	Target recognition
Li, wu, and Du (2017)	DRNN	Anomaly detection
Mou, Ghamisi and Zhu(2017)	DL	Image classification
Santara et al (2017)	DSL	Image classification
Makantasis et al (2015)	DCNN	Image classification
Hu, Huang, wei, zhang, and li (2015)	USL	Image classification
Tao, pan, Li and zou(2015)	DBN	Image classification
Chen, Zhao and Zou(2015)	DBN	Spectral classification
Chen, lin, Zhao, Wang, and Gu (2017)	DL	Image classification
Ghamisi, Chen, and Zhu, (2016)	CNN	Image classification
He, Zhang, Ren and Sun, (2016)	DL	Image recognition
Girshick, Donahue, Darrell and Malik, (2016)	CNN	Object detection
Long, Shelhamer and Darrell, (2015)	CNN	Semantic segmentation
Noh, Hong and Han, (2015)	CNN	Semantic segmentation
Chen, Jiang, Li, and Ghamisi (2016)	CNN	Feature extraction & classification
Kampftmeyer, SAlberg and Jenssen (2016)	DCNN	Semantic segmentation
Zhong, Yang, Huang, Zhong and chen (2016)	CNN	Image fusion

Survey Researches that applied deep learning techniques in computer vision

In this section we have subjected our search to only survey and review researches that recently applied deep learning techniques in computer vision. Moreover, we have strictly also concentered on where the research has conducted. To the base of our knowledge and findings in this work shows that higher percentage of computer vision researches are conducted in China while the remaining smaller percentage are shared among the rest. However, it comes to our noticed also that no one researches that was conducted in Africa in respect to computer vision.

Table 3: Survey Researches

Author and date	Techniques	Country	Description
Ma, *et al.*, (2019)	Deep learning	China	Mata analysis and review
Zhu *et al.*, (2017)	Deep learning	China	Comprehensive review
Tsagkatakis *et al.*, (2019)	Deep learning		Survey
Ball, Anderson and Chan., (2019)	Deep learning	China	Comprehensive survey
Song, Gao, Zhu And Ma (2019)	CNN	China	Survey
Hyedari and Mountrakis (2019)	DNN		Meta-analysis
Zhang, Zhang And Du (2020)	Deep learning	China	Technical tutorial
Lu, Sun, and Zhang (2019)	CNN	China	Feature aggregation
Paoletti, Haut and Plaz (2019)	Deep learning		Review

MIJRD Multidisciplinary International Journal of Research and Development
Multidisciplinary International Journal of Research and Development
Volume: 01 / Issue: 01 / 2021 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

Parikh, Patel and Patel, (2020)	Deep learning		Review
Li *et al.*, (2019)	Deep learning	China	Overview
Pashae, Kamangir, Starck And Tissot, (2020)	Deep learning		Review
Li, Zhang, Xue, Jiang and Shen (2018)	Dee learning	China	Survey
Liu *et al.*, (2018)	Deep learning	China	Advances and Feature
Rawat and Wang, (2017)	DCNN	India	Comprehensive survey
Xiao *et al.*, (2017).	DL	China	Comprehensive review
Athanasios *et al.*, (2018)	DL		Survey
Xiangwei, Doyen and Steven (2019)	DL	China	Recent advances
Lincheng et al., (2019)	DL	China	Survey
Accoss-Garcia et al., (2018)	DL	Spain	Analysis
Zhao, Feng, Wu and Yan (2017)	DL	China	Survey
Payal *et al.*, (2020)	DL		Survey
Jiao *et al.*, (2019)	DL	China	Survey
Abhishek et al., (2021)	DL	Canada	Survey
Vipul and Roohie, (2020)	DL	India	Review

Softwares for Compuetr Vision

Many softwares are available for the implementation of deep learning algorithms in computer vision researches. In this work we review some of the most recently applied softwares for computer vision. 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. (Jude and Vania, 2017).

Datasets used in Computer Vision

DL researches require huge amount of data to make correct decision. There are many datasets online for different application domain. In computer vision the most common once are; ImageNet with 1000 classes of images prepared for object detection and classification researches. MNIST are gray scale images with 10 different classes of image prepared for hand written digit classification, Microsoft COCO with 80 different image classes prepared for object detection, Google Open images with 350 classes of sample images applied in image segmentation and object detection, Kinetics with 400 samples prepared for human action detection researches, YouTube8m with 8 million classes of videos for video classification. Caltech consist of 101/256 sample of images, CIFAR consists of 32x32 RGB images of various classes, COIL is an RGB natural image dataset used for object classification. In the area of remote sensing many datasets are also available and used by many experts in computer vision to train deep learning algorithm for image classification, object detection and scene classification. Zurich summer data set it consist of 20 images acquired in Zurich Switzerland in 2002 which can be obtained from (Volpi, 2017). ISPRS 2D semantic labeling challenge which consist of an average pixel values of 2,000 X 3,000 in which 17 tiles are labeled and other half are not labeled. These data set can be obtained from (ISPRS, 2017). Zeebruges dataset, this dataset consists of 10,000 X 10,000-pixel value in which all the image are labeled. (Xiao *et al*, 2017). UC

MIJRD Multidisciplinary International Journal of Research and Development
Multidisciplinary International Journal of Research and Development
Volume: 01 / Issue: 01 / 2021 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

Merced dataset. This data set consist of aerial images with 256 X 256 pixel values which consist of 21 classes and each class is having 100 images. This dataset can be obtained from (NSf, 2010) there are used and applied for scene classification. Northwestern Polytechnic University Remote sensing image scene classification dataset this dataset consists of 31,500 aerial image with 45 different scene classes which are used and applied for scene classification and is obtainable from (EScience, 2016) SARPTICAL dataset this dataset is used in image registration and matching based research. (Xia *et al,* 2017). PASCAL VOC it contains 20 categories with four (4) classes of vehicles, animals, people and household objects introduced in 2005 used for object detection researches. VISDrone 2018 it was introduced in 2018 from China, consist of images and videos for object detection and tracking. ETH is a pedestrian datasets consist of 1804 frames on three classes of videos (Vipul and Roohie, 2020). INRIA is also a pedestrian detection datasets consist of 2120 images in which 1832 images for training and 288 for testing (Vipul and Roohie, 2020). PASCAL FACE datasets consist of 1335 labeled faces from 851 different categories of images it is widely applied in facial recognition researches (Vipul and Roohie, 2020) and FDDB datasets is also facial detection datasets consist of 5171 faces classified into 2845 images.

JOURNALS REVIEWED

In this section we have subjected our search to only top jounals in computer vision from IEEE, Elservier, Science Direct, conference proceedings and other related journals which are almost thirty three journals including few conference were reviewed in this work as shown in the table below;

Table 4: Journal reviewed

S/N	Title	Publisher
1.	IEEE Geoscience and Remote sensing letter	**IEEE**
2.	ISPRS Journal of photogrammetry and remote sensing	ISPRS
3.	IEEE international conference on mechatronic and Automation	IEEE
4.	Neutral Networks	ELSEVIER
5.	IEEE Conference on Computer Vision and Pattern Recognition	IEEE
6.	Advances in Neutral Information Processing System	ELSEVIER
7.	Arxiv preprint	ARVXIV
8.	Information fusion	ELSEVIER
9.	IEEE Geoscience and Remote Sensing Management	IEEE
10.	IEEE Transaction of Geoscience and Remote Sensing	ELSEVIER
11.	Internal Journal of Remote Sensing	IEEE
12.	Proceeding in Computer Science	IJRS
13.	Applied science	IEEE
14.	IEEE international Geoscience and Remote Sensing Symposium	ELSEVIER
15.	Remote Sensing	IEEE
16.	IEEE Geoscience and Remote Sensing Magazine	ELSEVIER
17.	Sensors	
18.	Journal of Applied Remote Sensing	

Volume: 01 / Issue: 01 / 2021 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

19.	Big Earth Data	IEEE
20.	International Journal of Image and Data Fusion	ELSEVIER
21.	Remote Sensing and Image Classification	JARS
22.	Neutral Computation	BED
23.	Computational intelligence and Neuron Hindawi	IJIDF
24.	IEEE Transaction on Pattern Analysis and Machine Intelligence	ELSEVIER
25.	Neurocomputing	ELSEVIER
26.	Journal of bag data Springer	HINDAWI
27.	Springer International Publishing	IEEE
28.	Computer Vision	ELSEVIER
29.	American Association for the Advancement of Science: Science	ELSEVIER
30.	Journal of machine learning research	SPRINGER
31.	IEEE Journal of Selected top application on Earth observation and remote sensing	SPRINGER
		ELSEVIER
		SCIENCE
		JMLR
		IEEE

CONCLUSION

In this work we conducted a thorough reviw in the application of deep learning techniques in computer vision. We have subjected our serch towards various categories of deep learning algoriths together with their associated architectures that are applied in computer vision researches, we have used systematic format of literature reviw and explored critically the state-of the-art in all aspect of computer vision and also explored survey and review researches in the state-of-art. furthermore, we have summarized the major softwares and toolboxes use for the implementation of computer researches in addition to the datasets that are suitable for all aspect of researches in computer vision.

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Volume: 01 / Issue: 01 / 2021 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

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