ENHANCED FASTER REGION-BASED CONVOLUTIONAL NEURAL NETWORK FOR OIL PALM TREE DETECTION

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Doctor of Philosophy

UNIVERSITI MALAYSIA PAHANG

SUPERVISOR'S DECLARATION

I hereby declare that I have checked this thesis and in my opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Doctor of Philosophy.

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STUDENT'S DECLARATION

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at University Malaysia Pahang or any other institution.

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ABSTRAK

Pokok kelapa sawit adalah tanaman ekonomi yang penting di Malaysia. Salah satu proses audit dalam pengurusan ladang adalah mengira jumlah pokok kelapa sawit. Ia dapat membantu pengurus meramal hasil tanaman dan jumlah baja dan tenaga kerja yang diperlukan. Bagaimanapun, pendekatan yang sedang digunakan dalam mengira kelapa sawit adalah secara manual dengan bantuan perisian GIS, yang merupakan tugas yang leceh dan tidak efisien untuk ladang berskala besar. Bagi mengatasi masalah yang tidak cekap dalam pengiraan secara manual, para penyelidik mencadangkan kaedah pengiraan automatik berdasarkan pemprosesan gambar dan pembelajaran mesin. Walau bagaimanapun, kaedah pemprosesan gambar tradisional dan pembelajaran mesin menggunakan kaedah pengekstrakan ciri buatan tangan, hanya dapat mengekstrak ciri-ciri tahap rendah-menengah dari gambar, dan kekurangan kemampuan generalisasi yang berlaku untuk satu aplikasi perlu diprogramkan semula untuk aplikasi lain. Pendekatan pengekstrakan ciri yang digunakan secara meluas adalah transformasi ciri invarian skala (SIFT), corak binari tempatan (LBP), dan histogram kecerunan berorientasi (HOG), yang biasanya mencapai ketepatan rendah kerana ciri terhadnya mewakili kemampuan dan tanpa kemampuan generalisasi. Oleh itu, penyelidikan ini bertujuan untuk menutup jurang kajian dengan meneroka algoritma pengesanan objek berasaskan pembelajaran mendalam dan rangkaian saraf konvolusional klasik (CNN) untuk membina kerangka pengesanan dan pengiraan pokok kelapa sawit berasaskan pembelajaran secara mendalam. Kajian ini mencadangkan teknik baru iaitu kaedah pembelajaran mendalam berdasarkan RCNN Lebih Cepat untuk pengesanan dan pengiraan pokok kelapa sawit. Untuk mengurangkan masalah overfitting semasa latihan, kajian ini menggunakan kaedah pemprosesan gambar untuk menambah set data latihan dengan membalikkan gambar secara rawak dan meningkatkan kontras dan kecerahan data. Model pembelajaran pemindahan ResNet50 digunakan untuk melatih rangkaian Faster RCNN untuk mendapatkan bobot pengiraan pokok kelapa sawit secara automatik. Model yang dicadangkan disahkan pada kumpulan data pengujian dengan tiga wilayah pokok kelapa sawit masing-masing dengan pokok yang matang, muda dan bercampur (muda dan matang). Hasil pengesanan juga dibandingkan dengan dua kaedah pembelajaran mesin ANN, SVM, dan kaedah TM berasaskan pemprosesan gambar, masing-masing. Model Faster RCNN yang dicadangkan menunjukkan hasil yang menjanjikan dari pengesanan dan pengiraan pokok kelapa sawit di mana ia mencapai ketepatan keseluruhan hingga 97% dalam set data pengujian dan 97.2% di kawasan pohon kelapa sawit campuran, dan 96.9% pada pokok kelapa sawit yang matang dan muda wilayah, manakala kaedah tradisional ANN, SVM, dan TM kurang dari 90%. Perbandingan ketepatan menunjukkan bahawa model EFRCNN yang dicadangkan mengungguli kaedah tradisional ANN, SVM, dan TM, dan berpotensi digunakan dalam penghitungan ladang kelapa sawit di kawasan yang luas.

ABSTRACT

Oil palm trees are important economic crops in Malaysia. One of the audit procedures is to count the number of oil palm trees for plantation management, which helps the manager predict the plantation yield and the amount of fertilizer and labor force needed. However, the current counting method for oil palm tree plantation is manually counting using GIS software, which is tedious and inefficient for large scale plantation. To overcome this problem, researchers proposed automatic counting methods based on machine learning and image processing. However, traditional machine learning and image processing methods used handcrafted feature extraction methods. It can only extract low-middle level features from the image and lack of generalization ability. It's applicable only for one application and will need reprogramming for other applications. The widely used feature extraction methods are local binary patterns (LBP), scale-invariant feature transform (SIFT), and the histogram of oriented gradients (HOG), which usually achieve low accuracy because of their limited feature representation ability and without generalization capability. Hence, this research aims to close the research gaps by exploring the deep learning-based object detection algorithm and the classical convolutional neural network (CNN) to build an automatic deep learning-based oil palm tree detection and counting framework. This study proposed a new deep learning method based on Faster RCNN for oil palm tree detection and counting. To reduce the overfitting problem during the training, this study uses the image processing method to augment the training dataset by random flipping the image and to increase the data's contrast and brightness. The transfer learning model of ResNet50 was used as the CNN backbone and the Faster RCNN network was retrained to get the weight for automatic oil palm tree counting. To improve the performance of Faster RCNN, feature concatation method was used to integrate the high-level and low-level feature from ResNet50. The proposed model validated the testing dataset of three palm tree regions with mature, young, and mixed mature and young palm trees. The detection results were compared with two machine learning methods of ANN, SVM, image processing-based TM method, and the original Faster RCNN model respectively. The proposed enhanced Faster RCNN model shows a promising result of oil palm tree detection and counting. It achieved an overall accuracy of 97% in the testing dataset, 97.2% in the mixed palm tree region, and 96.9% in the mature and young palm tree region, while the traditional ANN, SVM, and TM methods are less than 90%. The accuracy of comparison reveals that the proposed EFRCNN model outperforms the Faster RCNN and the traditional ANN, SVM, and TM methods. It has the potential to apply in counting a large area of oil palm tree plantation.

TABLE OF CONTENT

REFERENCES

A. Krizhevsky, I. S., and G. Hinton. (2012). Imagenet classification with deep convolutional neural networks. Paper presented at the Advances in Neural Information Processing Systems, Lake Tahoe, Nevada.

Alam, A., Er, A. C., & Begum, H. (2015). Malaysian oil palm industry: prospect and problem. *Journal of Food, Agriculture & Environment, 13*(2), 143-148.

Ali, M. A., & Thai, K. W. (2017). *Automated fruit grading system.* Paper presented at the 2017 IEEE 3rd International Symposium in Robotics and Manufacturing Automation (ROMA).

Altwaijry, H., Trulls, E., Hays, J., Fua, P., & Belongie, S. (2016). *Learning to match aerial images with deep attentive architectures.* Paper presented at the The IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

Aquino, A., Millan, B., Diago, M.-P., & Tardaguila, J. (2018). Automated early yield prediction in vineyards from on-the-go image acquisition. *Computers and electronics in agriculture, 144*, 26-36.

Arti Singh, B. G., Asheesh Kumar Singh, Soumik Sarkar. (2016). Machine Learning for High-Throughput Stress Phenotyping in Plants. *Trends in Plant Science, 21*(2), 110-124. doi:https://doi.org/10.1016/j.tplants.2015.10.015

B, O. A., Penatti, Nogueira, K., A, J., & Santos, d. (2015). *Do deep features generalize from everyday objects to remote sensing and aerial scenes domains?* Paper presented at the The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops.

Bai, T., Pang, Y., Wang, J., Han, K., Luo, J., Wang, H., Zhang, H. (2020). An Optimized Faster R-CNN Method Based on DRNet and RoI Align for Building Detection in Remote Sensing Images. *Remote Sensing, 12*(5), 762.

Barcelos, E., Rios, S. d. A., Cunha, R. N., Lopes, R., Motoike, S. Y., Babiychuk, E., Kushnir, S. (2015). Oil palm natural diversity and the potential for yield improvement. *Frontiers in plant science, 6*, 190.

Bazi, Y., Malek, S., Alajlan, N., & AlHichri, H. (2014). *An automatic approach for palm tree counting in UAV images.* Paper presented at the 2014 IEEE Geoscience and Remote Sensing Symposium.

Benjdira, B., Khursheed, T., Koubaa, A., Ammar, A., & Ouni, K. (2019). *Car detection using unmanned aerial vehicles: Comparison between faster r-cnn and yolov3.* Paper presented at the 2019 1st International Conference on Unmanned Vehicle Systems-Oman (UVS).

Boonpook, W., Tan, Y., Ye, Y., Torteeka, P., Torsri, K., & Dong, S. (2018). A Deep Learning Approach on Building Detection from Unmanned Aerial Vehicle-Based Images in Riverbank Monitoring. *Sensors, 18*(11), 3921-3933. doi:10.3390/s18113921

Caballero, D., Calvini, R., & Amigo, J. M. (2020). Hyperspectral imaging in crop fields: precision agriculture. In *Data Handling in Science and Technology* (Vol. 32, pp. 453-473): Elsevier.

Campisi, R. D. E. P. E. M. P. (2019). Convolutional Neural Network for Finger-Vein-Based Biometric Identification. *IEEE Transactions on Information Forensics and Security, 14*(2), 360 - 373. doi:10.1109/TIFS.2018.2850320

Cao, R., Zhu, J., Tu, W., Li, Q., Cao, J., Liu, B., Qiu, G. (2018). Integrating Aerial and Street View Images for Urban Land Use Classification. *Remote Sensing, 10*(10), 1553-1575. doi:https://doi.org/10.3390/rs10101553

Cardona, D. A. B., Nedjah, N., & Mourelle, L. M. (2017). Online phoneme recognition using multi-layer perceptron networks combined with recurrent non-linear autoregressive neural networks with exogenous inputs. *Neurocomputing, 265*, 78-90.

Carrio, A., Sampedro, C., Rodriguez-Ramos, A., & Campoy, P. (2017). A review of deep learning methods and applications for unmanned aerial vehicles. *Journal of Sensors, 2017*.

Castelluccio, M., Poggi, G., Sansone, C., & Verdoliva, L. (2015). Land use classification in remote sensing images by convolutional neural networks. *arXiv preprint arXiv:1508.00092.*

Cheang, E. K., Cheang, T. K., & Tay, Y. H. (2017). Using convolutional neural networks to count palm trees in satellite images. *arXiv preprint arXiv:1701.06462*.

Chen, Y., Ribera, J., & Delp, E. J. (2018, 8-10 April 2018). *Estimating Plant Centers Using A Deep Binary Classifier.* Paper presented at the 2018 IEEE Southwest Symposium on Image Analysis and Interpretation (SSIAI), Las Vegas, NV, USA.

Chena, Q., Wang, L., Wu, Y., Wu, G., Guo, Z., & Waslander, S. L. (2019). Aerial imagery for roof segmentation: A large-scale dataset towards automatic mapping of buildings. *ISPRS Journal of Photogrammetry Remote Sensing Letters, 147*, 42-55.

Cheng, G., Han, J., & Lu, X. (2017). Remote sensing image scene classification: benchmark and state of the art. *Proceedings of the IEEE, 105*(10), 1865-1883. doi:10.1109/JPROC.2017.2675998

Cheng, G., Han, J., Zhou, P., & Guo, L. (2014). Multi-class geospatial object detection and geographic image classification based on collection of part detectors. *ISPRS Journal of Photogrammetry Remote Sensing Letters, 98*, 119-132. doi:https://doi.org/10.1016/j.isprsjprs.2014.10.002

Cheng, G., Yang, C., Yao, X., Guo, L., & Han, J. (2018). When deep learning meets metric learning: remote sensing image scene classification via learning discriminative CNNs. *IEEE Transactions on Geoscience Remote Sensing, 56*(5), 2811-2821.

Chong, K. L., Kanniah, K. D., Pohl, C., & Tan, K. P. (2017). A review of remote sensing applications for oil palm studies. *Geo-spatial Information Science, 20*(2), 184-200. doi:https://doi.org/10.1080/10095020.2017.1337317

Cracknell, A. P., Kanniah, K. D., Tan, K. P., & Wang, L. (2015). Towards the development of a regional version of MOD17 for the determination of gross and net primary productivity of oil palm trees. *International journal of remote sensing, 36*(1), 262-289. doi:https://doi.org/10.1080/01431161.2014.995278

Daliman, S., Abu-Bakar, S., & Azam, S. M. N. (2016). *Development of young oil palm tree recognition using Haar-based rectangular windows.* Paper presented at the IOP

Conference Series: Earth and Environmental Science.

Dalponte, M., Ene, L. T., Marconcini, M., Gobakken, T., & Næsset, E. (2015). Semi-supervised SVM for individual tree crown species classification. *ISPRS Journal of Photogrammetry and Remote Sensing, 110*, 77-87. doi:10.1016/j.isprsjprs.2015.10.010

Darby, S. (2014). Palm oil facts and figures. *Sime Darby Plantation: Profile and Fact Sheets; Sime Darby: Kuala Lumpur, Malaysia*, 1-8.

Devi, T. G., Neelamegam, P., & Sudha, S. (2017). *Image Processing System for Automatic Segmentation and Yield Prediction of Fruits using Open CV.* Paper presented at the 2017 International Conference on Current Trends in Computer, Electrical, Electronics and Communication (CTCEEC).

Duarte, D., Nex, F., Kerle, N., & Vosselman, G. (2018). Multi-Resolution Feature Fusion for Image Classification of Building Damages with Convolutional Neural Networks. *Remote Sensing, 10*(10), 1636-1661.

El-Sawy, A., Hazem, E.-B., & Loey, M. (2016). *CNN for handwritten arabic digits recognition based on LeNet-5.* Paper presented at the International conference on advanced intelligent systems and informatics.

Fadaeddini, A., Eshghi, M., & Majidi, B. (2018, 28 Feb.-2 March 2018). *A deep residual neural network for low altitude remote sensing image classification.* Paper presented at the 2018 6th Iranian Joint Congress on Fuzzy and Intelligent Systems (CFIS),, Kerman, Iran.

Fadilah, N., Saleh, J. M., Ibrahim, H., & Halim, Z. A. (2012, 12-14 June 2012). *Oil palm fresh fruit bunch ripeness classification using artificial neural network.* Paper presented at the 2012 4th International Conference on Intelligent and Advanced Systems (ICIAS2012), Kuala Lumpur, Malaysia.

García, L., Parra, L., Jimenez, J. M., Lloret, J., & Lorenz, P. (2020). IoT-Based Smart Irrigation Systems: An Overview on the Recent Trends on Sensors and IoT Systems for Irrigation in Precision Agriculture. *Sensors, 20*(4), 1042.

Gopalakrishnan, K., Gholami, H., Vidyadharan, A., Choudhary, A., & Agrawal, A. (2018). Crack damage detection in unmanned aerial vehicle images of civil infrastructure using pre-trained deep learning model. *International Journal for Traffic Transport Engineering, 8*(1), 1-14. doi: http://dx.doi.org/10.7708/ijtte.2018.8(1).01

Griffiths, D., & Boehm, J. (2018, 4–7 June 2018). *Rapid object detection systems, utilising deep learning and unmanned aerial systems (UAS) for civil engineering applications.* Paper presented at the International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences-ISPRS Archives, Riva del Garda, Italy.

H-J, Y. (2015). Deep convolution neural networks in computer vision: review. *IEIE Transactions on Smart Processing and Computing, 4*(1), 35-43.

Hai, T. C. (2002). The palm oil industry in Malaysia. *WWF, Malaysia.*

Han, W., Feng, R., Wang, L., & Cheng, Y. (2018). A semi-supervised generative framework with deep learning features for high-resolution remote sensing image scene classification. *ISPRS Journal of Photogrammetry Remote Sensing Letters, 145*, 23-43.

Hansen, S. B., Padfield, R., Syayuti, K., Evers, S., Zakariah, Z., & Mastura, S. (2015). Trends in global palm oil sustainability research. *Journal of Cleaner Production, 100*, 140-149.

Hastie, T. T., Robert. Friedman, Jerome. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. New York, NY: Springer.

Hilal Tayara, K. T. C. (2018). Object Detection in Very High-Resolution Aerial Images Using One-Stage Densely Connected Feature Pyramid Network. *Sensors, 18*(10), 3341-3358.

Hosang, J., Benenson, R., & Schiele, B. (2017). *Learning non-maximum suppression.* Paper presented at the Proceedings of the IEEE conference on computer vision and pattern recognition.

Hossain, M. D., & Chen, D. (2019). Segmentation for object-based image analysis (obia): A review of algorithms and challenges from remote sensing perspective. *ISPRS Journal of Photogrammetry and Remote Sensing, 150*, 115-134.

Howard B. Demuth, M. H. B., Orlando De Jess, Martin T. Hagan. (2014). *Neural Network Design*: Martin Hagan , USA

Hu, F., Xia, G.-S., Hu, J., & Zhang, L. (2015). Transferring deep convolutional neural networks for the scene classification of high-resolution remote sensing imagery. *Remote Sensing, 7*(11), 14680-14707. doi:10.3390/rs71114680

Iqbal, S. M., Gopal, A., Sankaranarayanan, P., & Nair, A. B. (2015). *Estimation of size and shape of citrus fruits using image processing for automatic grading.* Paper presented at the 2015 3rd International Conference on Signal Processing, Communication and Networking (ICSCN).

Jinwang Wang, W. G., Ting Pan, Huai Yu, Lin Duan, Wen Yang. (2018). *Bottle Detection in the Wild Using Low-Altitude Unmanned Aerial Vehicles.* Paper presented at the 2018 21st International Conference on Information Fusion (FUSION), Cambridge, UK.

Jiuxiang Gu, Z. W., Jason Kuen, Lianyang Ma. (2018). Recent advances in convolutional neural networks. *Pattern Recognition, 77*, 354-377.

Jorge Calvo-Zaragoza, A.-J. G. (2019). A selectional auto-encoder approach for document image binarization. *Pattern Recognition, 86*, 37-47. doi:https://doi.org/10.1016/j.patcog.2018.08.011

Kaiming He, X. Z., Shaoqing Ren, Jian Sun. (2015). *Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification.* Paper presented at the The IEEE International Conference on Computer Vision (ICCV), Piscataway.

Kaiming He, X. Z., Shaoqing Ren, Jian Sun. (2016). *Deep residual learning for image recognition*. Paper presented at the The IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

Kamusoko, C. (2017). *Importance of Remote Sensing and Land Change Modeling for Urbanization Studies*. Singapore: Springer.

Karen Simonyan, A. Z. (2015). *Very deep convolutional networks for large-scale image recognition*.

Ke, Y., & Quackenbush, L. J. (2011). A review of methods for automatic individual tree-crown detection and delineation from passive remote sensing. *International journal of remote sensing, 32*(17), 4725-4747.

Kellenberger, B., Marcos, D., & Tuia, D. (2018). Detecting mammals in UAV images: Best practices to address a substantially imbalanced dataset with deep learning. *Remote Sensing of Environment, 216*, 139-153. doi:https://doi.org/10.1016/j.rse.2018.06.028

Kemker, R., Salvaggio, C., & Kanan, C. (2018). Algorithms for semantic segmentation of multispectral remote sensing imagery using deep learning. *ISPRS Journal of Photogrammetry Remote Sensing Letters, 145*, 60-77. doi:https://doi.org/10.1016/j.isprsjprs.2018.04.014

Kerkech, M., Hafiane, A., & Canals, R. (2018). Deep leaning approach with colorimetric spaces and vegetation indices for vine diseases detection in UAV images. *Computers Electronics in Agriculture, 155*, 237-243. doi:https://doi.org/10.1016/j.compag.2018.10.006

Korom, A., Phua, M., Hirata, Y., & Matsuura, T. (2014). *Extracting oil palm crown from WorldView-2 satellite image.* Paper presented at the IOP Conference Series: Earth and Environmental Science.

Kushairi, A., Loh, S. K., Azman, I., Hishamuddin, E., Ong-Abdullah, M., Izuddin, Z., Parveez, G. K. A. (2018). Oil palm economic performance in Malaysia and R&D progress in 2017. *Journal of Oil Palm Research, 30*(2), 163-195.

Lavania, S., & Matey, P. S. (2015). *Novel method for weed classification in maize field using Otsu and PCA implementation.* Paper presented at the 2015 IEEE International Conference on Computational Intelligence & Communication Technology.

LeCun, Y.-L. B. N. L. R. F. B. J. P. Y. (2011). *Ask the locals: Multi-way local pooling for image recognition.* Paper presented at the 2011 International Conference on Computer Vision.

LeCun, Y. (November 2013). LeNet-5, convolutional neural networks. *Retrieved 16*

Li, W., Dong, R., & Fu, H. (2019). Large-Scale Oil Palm Tree Detection from High-Resolution Satellite Images Using Two-Stage Convolutional Neural Networks. *Remote Sensing, 11*(1), 11-30. doi:https://doi.org/10.3390/rs11010011

Li, W., Fu, H., Yu, L., & Cracknell, A. (2016). Deep learning based oil palm tree detection and counting for high-resolution remote sensing images. *Remote Sensing, 9*(1), 22-35. doi:https://doi.org/10.3390/rs9010022

Li, X., Yao, X., & Fang, Y. (2018). Building-A-Nets: Robust Building Extraction From High-Resolution Remote Sensing Images With Adversarial Networks. *IEEE Journal of Selected Topics in Applied Earth Observations Remote Sensing Letters, 11*(10), 3680-3687. doi:10.1109/JSTARS.2018.2865187

Lin Min, C. Q., Yan Shuicheng. (2013). Network in network. *arXiv preprint arXiv, 1312.4400.*

Liu, K., & Mattyus, G. (2015). Fast Multiclass Vehicle Detection on Aerial Images. *IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, 12*(9), 1938-1942.

Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.-Y., & Berg, A. C. (2016). *Ssd: Single shot multibox detector.* Paper presented at the European conference on computer vision.

Liu, X., Jiang, H., Chen, J., Chen, J., Zhuang, S., & Miao, X. (2018, 12-15 June 2018). *Insulator Detection in Aerial Images Based on Faster Regions with Convolutional Neural Network.* Paper presented at the 2018 IEEE 14th International Conference on Control and Automation (ICCA), Anchorage, AK, USA.

Liu, Y., Sun, P., Highsmith, M. R., Wergeles, N. M., Sartwell, J., Raedeke, A., Shang, Y. (2018, 18-21 June 2018). *Performance comparison of deep learning techniques for recognizing birds in aerial images.* Paper presented at the 2018 IEEE Third International Conference on Data Science in Cyberspace (DSC), Guangzhou, China.

Makantasis, K., Karantzalos, K., Doulamis, A., & Doulamis, N. (2015, 26-31 July 2015). *Deep supervised learning for hyperspectral data classification through convolutional neural networks.* Paper presented at the 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS).

Maluin, F. N., Hussein, M. Z., & Idris, A. S. (2020). An Overview of the Oil Palm Industry: Challenges and Some Emerging Opportunities for Nanotechnology Development. *Agronomy, 10*(3), 356.

Manandhar, A., Hoegner, L., & Stilla, U. (2016). Palm tree detection using circular autocorrelation of polar shape matrix. *ISPRS Annals of Photogrammetry, Remote Sensing Spatial Information Sciences, 3*, 465-472.

Marmanis, D., Datcu, M., Esch, T., & Stilla, U. (2016). Deep learning earth observation classification using ImageNet pretrained networks. *IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, 13*(1), 105-109.

Marmanis, D., Wegner, J. D., Galliani, S., Schindler, K., Datcu, M., & Stilla, U. (2016). Semantic segmentation of aerial images with an ensemble of CNNs. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 3*, 473-480.

Matthew D. Zeiler, R. F. (2013). Stochastic Pooling for Regularization of Deep Convolutional Neural Networks. *arXiv：1301． 3557vl*.

Mhaski, R. R., Chopade, P., & Dale, M. (2015). *Determination of ripeness and grading of tomato using image analysis on Raspberry Pi.* Paper presented at the 2015 Communication, Control and Intelligent Systems (CCIS).

Miranda, V., Pina, P., Heleno, S., Vieira, G., Mora, C., & Schaefer, C. E. (2020). Monitoring recent changes of vegetation in Fildes Peninsula (King George Island, Antarctica) through satellite imagery guided by UAV surveys. *Science of The Total Environment, 704*, 135295.

Mnih, V. (2013). *Machine learning for aerial image labeling*: University of Toronto (Canada).

Mohammad Mehedi Hassan, M. G. R. A., Md. Zia Uddin, Shamsul Huda, Ahmad Almogren, Giancarlo Fortino. (2019). Human emotion recognition using deep belief network architecture. *Information Fusion, 51*, 10-18. doi:https://doi.org/10.1016/j.inffus.2018.10.009

Mohan, V. S., Sowmya, V., & Soman, K. P. (2018). *Deep Neural Networks as Feature Extractors for Classification of Vehicles in Aerial Imagery.* Paper presented at the 2018 5th International Conference on Signal Processing and Integrated Networks (SPIN), Noida, India.

Mou, L., & Zhu, X. X. (2018). Vehicle Instance Segmentation from Aerial Image and Video Using a Multi-Task Learning Residual Fully Convolutional Network. *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, 56*(11), 6699-6711.

Mubin, N. A., Nadarajoo, E., Shafri, H. Z. M., & Hamedianfar, A. (2019). Young and mature oil palm tree detection and counting using convolutional neural network deep learning method. *International journal of remote sensing, 40*(19), 7500-7515.

Nair, V., & Hinton, G. E. (2010). *Rectified linear units improve restricted Boltzmann machines*, Haifa.

Najibi, M., Samangouei, P., Chellappa, R., & Davis, L. S. (2017). *Ssh: Single stage headless face detector.* Paper presented at the Proceedings of the IEEE International Conference on Computer Vision.

Nambiappan, B., Ismail, A., Hashim, N., Ismail, N., Nazrima, D., Abdullah, N., Ain, N. (2018). Malaysia: 100 years of resilient palm oil economic performance. *Journal of Oil Palm Research, 30*(1), 13-25. doi:https://doi.org/10.21894/jopr.2018.0014

Neupane, B., Horanont, T., & Hung, N. D. (2019). Deep learning based banana plant detection and counting using high-resolution red-green-blue (RGB) images collected from unmanned aerial vehicle (UAV). *PloS one, 14*(10).

Nisar, H., Yang, H. Z., & Ho, Y. K. (2015). Predicting yield of fruit and flowers using digital image analysis. *Indian Journal of Science and Technology, 8*, 32.

Oshri, B., Hu, A., Adelson, P., Chen, X., Dupas, P., Weinstein, J., Ermon, S. (2018). Infrastructure Quality Assessment in Africa using Satellite Imagery and Deep Learning. *arXiv preprint arXiv:.00894.* doi:10.1145/3219819.3219924

Paikekari, A., Ghule, V., Meshram, R., & Raskar, V. (2016). Weed detection using image processing. *International Research Journal of Engineering and Technology (IRJET), 3*(3), 1220-1222.

Pakarpour Rayeni, F., & Seraj, A. A. (2016). Review of the leafhopper genus Neoaliturus distant (Hemiptera: Cicadellidae: Deltocephalinae) from Iran. *Journal of Insect Biodiversity and Systematics, 2*(4), 381-394.

Pan, M., Liu, Y., Cao, J., Li, Y., Li, C., & Chen, C.-H. (2020). Visual Recognition Based on Deep Learning for Navigation Mark Classification. *IEEE Access, 8*, 32767-32775.

R, D. J. D. W. S. (2009). *Imagenet: A large-scale hierarchical image database*, New York.

RaechelWhite, A. (2019). Human expertise in the interpretation of remote sensing data: A cognitive task analysis of forest disturbance attribution. *International Journal of Applied Earth Observation and Geoinformation, 74*, 37-44. doi:https://doi.org/10.1016/j.jag.2018.08.026

Raj, R., Kar, S., Nandan, R., & Jagarlapudi, A. (2020). Precision Agriculture and Unmanned Aerial Vehicles (UAVs). In *Unmanned Aerial Vehicle: Applications in Agriculture and Environment* (pp. 7-23): Springer.

Ram, B., Rashid, M., Lakhwani, K., & Kumar, S. S. (2020). Health Detection of Wheat Crop

Using Pattern Recognition and Image Processing. *International Journal of Healthcare Information Systems and Informatics (IJHISI), 15*(2), 50-60.

Ramchoun, H., Idrissi, M. A. J., Ghanou, Y., & Ettaouil, M. (2016). Multilayer Perceptron: Architecture Optimization and Training. *IJIMAI, 4*(1), 26-30.

Razakarivonyb, S., & Jurie, F. (2016). Vehicle detection in aerial imagery: A small target detection benchmark. *Journal of Visual Communication Image Representation, 34*, 187-203. doi:https://doi.org/10.1016/j.jvcir.2015.11.002

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). *You only look once: Unified, real-time object detection.* Paper presented at the Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR).

Ren, S., He, K., Girshick, R., & Sun, J. (2017). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. *IEEE Transactions on Pattern Analysis & Machine Intelligence, 39(6)*, 1137-1149.

Rezaee, M., Zhang, Y., Mishra, R., Tong, F., & Tong, H. (2018). *Using a VGG-16 Network for Individual Tree Species Detection with an Object-Based Approach.* Paper presented at the 2018 10th IAPR Workshop on Pattern Recognition in Remote Sensing (PRRS), Beijing, China.

Rizeei, H. M., Shafri, H. Z., Mohamoud, M. A., Pradhan, B., & Kalantar, B. (2018). Oil palm counting and age estimation from WorldView-3 imagery and LiDAR data using an integrated OBIA height model and regression analysis. *Journal of Sensors, 2018*.

Romero, A., Gatta, C., & Camps-Valls, G. (2016a). Unsupervised deep feature extraction for remote sensing image classification. *IEEE Transactions on Geoscience Remote Sensing, 54*(3), 1349-1362. doi:10.1109/TGRS.2015.2478379

Romero, A., Gatta, C., & Camps-Valls, G. (2016b). Unsupervised deep feature extraction for remote sensing image classification. *IEEE Transactions on Geoscience Remote Sensing, 54*(3), 1349-1362.

Roselyne Ishimwe, K. A., F. Ahmed. (2014). Applications of Thermal Imaging in Agriculture—A Review. *Advances in Remote Sensing, 3*(2014), 128-140. doi: 10.4236/ars.2014.33011

Rottensteiner, F., Sohn, G., Jung, J., Gerke, M., Baillard, C., Benitez, S., & Breitkopf, U. (2012). The ISPRS benchmark on urban object classification and 3D building reconstruction. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 1*(3), 293-298.

Samarasinghe, S. (2016). *Neural Networks for Applied Sciences and Engineering.* New York: Auerbach Publications.

Satir, O., & Berberoglu, S. (2016). Crop yield prediction under soil salinity using satellite derived vegetation indices. *Field crops research, 192*, 134-143.

Sergey Ioffe, C. S. (2015). *Batch normalization: Accelerating deep network training by reducing internal covariate shift.* Paper presented at the ICML.

Sethy, P. K., Panda, S., Behera, S. K., & Rath, A. K. (2017). On tree detection, counting & post-harvest grading of fruits based on image processing and machine learning approach-a review. *International Journal of Engineering & Technology, 9*(2), 649-663.

Shafri, H. Z., Hamdan, N., & Saripan, M. I. (2011). Semi-automatic detection and counting of oil palm trees from high spatial resolution airborne imagery. *International journal of remote sensing, 32*(8), 2095-2115. doi:https://doi.org/10.1080/01431161003662928

Sheng, G., Yang, W., Xu, T., & Sun, H. (2012). High-resolution satellite scene classification using a sparse coding based multiple feature combination. *International journal of remote sensing, 33*(8), 2395-2412. doi:https://doi.org/10.1080/01431161.2011.608740

Suhaily, S., Jawaid, M., Khalil, H. A., Mohamed, A. R., & Ibrahim, F. (2012). A review of oil palm biocomposites for furniture design and applications: potential and challenges. *BioResources, 7*(3), 4400-4423.

Suksawat, B., & Komkum, P. (2015). *Pineapple quality grading using image processing and fuzzy logic based on Thai Agriculture Standards.* Paper presented at the 2015 International Conference on Control, Automation and Robotics.

Sukumar, P., & Ravi, D. S. (2016). Weed detection using image processing by clustering analysis. *International Journal of Emerging Technologies in Engineering Research (IJETER), 4*(5), 14-18.

Sun, X., Wu, P., & Hoi, S. C. (2018). Face detection using deep learning: An improved faster RCNN approach. *Neurocomputing, 299*, 42-50.

Sun, Y., Zhang, X., Xin, Q., & Huang, J. (2018). Developing a multi-filter convolutional neural network for semantic segmentation using high-resolution aerial imagery and LiDAR data. *ISPRS Journal of Photogrammetry Remote Sensing Letters, 143*, 3-14. doi:https://doi.org/10.1016/j.isprsjprs.2018.06.005

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Rabinovich, A. (2015). *Going deeper with convolutions.* Paper presented at the Proceedings of the IEEE conference on computer vision and pattern recognition.

Tang, J.-L., Chen, X.-Q., Miao, R.-H., & Wang, D. (2016). Weed detection using image processing under different illumination for site-specific areas spraying. *Computers and electronics in agriculture, 122*, 103-111.

Tanner, F., Colder, B., Pullen, C., Heagy, D., Eppolito, M., Carlan, V., Sallee, P. (2010). *Overhead imagery research data set—An annotated data library & tools to aid in the development of computer vision algorithms.* Paper presented at the 2009 IEEE Applied Imagery Pattern Recognition Workshop (AIPR 2009), Washington, DC.

Tayara, H., & Chong, K. T. (2018). Object Detection in Very High-Resolution Aerial Images Using One-Stage Densely Connected Feature Pyramid Network. *Sensors, 18*(10), 3341-3358.

Trujillano, F., Flores, A., Saito, C., Balcazar, M., & Racoceanu, D. (2018). *Corn classification using Deep Learning with UAV imagery. An operational proof of concept.* Paper presented at the 2018 IEEE 1st Colombian Conference on Applications in Computational Intelligence (ColCACI), Medellin, Colombia.

Uijlings, J. R., EA, K., Sande, V. D., Gevers, T., & Smeulders, A. W. (2013). Selective search for object recognition. *International Journal of Computer Vision, 104*(2), 154-171.

Volpi, M., & Tuia, D. (2018). Deep multi-task learning for a geographically-regularized semantic segmentation of aerial images. *ISPRS Journal of Photogrammetry Remote Sensing Letters, 144*, 48-60. doi:https://doi.org/10.1016/j.isprsjprs.2018.06.007

W, H. G. E. O. S. T. Y. (2006). A fast learning algorithm for deep belief nets. *Neural Computation, 18(7)*, 1527-1554.

Wang, J., Guo, W., Pan, T., Yu, H., Duan, L., & Yang, W. (2018). *Bottle Detection in the Wild Using Low-Altitude Unmanned Aerial Vehicles.* Paper presented at the 2018 21st International Conference on Information Fusion (FUSION), Cambridge, UK.

Wang, R., Xiao, X., Guo, B., Qin, Q., & Chen, R. (2018). An Effective Image Denoising Method for UAV Images via Improved Generative Adversarial Networks. *Sensors, 18*(7), 1985-2007. doi:10.3390/s18071985

Wang, Y., Zhu, X., & Wu, B. (2019). Automatic detection of individual oil palm trees from UAV images using HOG features and an SVM classifier. *International journal of remote sensing*, *40*(19), 7356-7370.

Xia, G.-S., Hu, J., Hu, F., Shi, B., Bai, X., Zhong, Y., & Zhang, L. (2017). AID: A benchmark data set for performance evaluation of aerial scene classification. *IEEE Transactions on Geoscience Remote Sensing Letters, 55*(7), 3965-3981. doi:10.1109/TGRS.2017.2685945

Xu, F. Z. B. D. L. Z. M. (2016). Weakly Supervised Learning Based on Coupled Convolutional Neural Networks for Aircraft Detection. *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, 54*(9), 5553 - 5563. doi:10.1109/TGRS.2016.2569141

Xu, Y., Yu, L., Li, W., Ciais, P., Cheng, Y., & Gong, P. (2020). Annual oil palm plantation maps in Malaysia and Indonesia from 2001 to 2016. *Earth System Science Data*, *12*(2), 847-867.

Y-Lan Boureau, J. P., Yann LeCun. (2010). *A Theoretical Analysis of Feature Pooling in Visual Recognition*. Paper presented at the International Conference on Machine Learning.

Zhao, Z.-Q., Zheng, P., Xu, S.-t., & Wu, X. (2019). Object detection with deep learning: A review. *IEEE transactions on neural networks and learning systems, 30*(11), 3212-3232.

Zhong, J., Lei, T., & Yao, G. (2017). Robust vehicle detection in aerial images based on cascaded convolutional neural networks. *Sensors, 17*(12), 2720-2737.

Zortea, M., Nery, M., Ruga, B., Carvalho, L. B., & Bastos, A. C. (2018). *Oil-Palm Tree Detection in Aerial Images Combining Deep Learning Classifiers.* Paper presented at the IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium.

Zou, Z., & Shi, Z. (2018). Random access memories: A new paradigm for target detection in high resolution aerial remote sensing images. *IEEE Transactions on Image Processing, 27*(3), 1100-1111. doi:10.1109/TIP.2017.2773199