International Journal For Technological Research In Engineering
Volume 6, Issue 3, November-2018 *ISSN (Online): 2347 - 4718*

DEEP LEARNING APPLICATION IN CROP MANAGEMENT: A SURVEY

Gunvantsinh D. Gohil[1], Gaurang S. Kharadi[2], Dhaval S. Thanki[3]
Assistant Professor, Department of Food and Processing Engineering, Junagadh Agricultural University, Junagadh, Gujarat, India

Abstract: Food security to increasing world population is major challenge to address. Food production has to be increased in great amount to deal with this worsening situations (FAO, 2009). Moreover, in parallel to bulk productivity, availability of nutritional quality food, protecting natural ecosystem are also required to be taken care of. More sustainable, precise and smart farming procedure is the need of time to address these challenges. Many technical advancements have been taken place in agriculture domain and more recent advancements are coming in to make this sector more efficient. Machine learning and artificial intelligent are such domains which have recently been aggressively applied in the field of agriculture. This paper presents the survey of various applications of machine learning techniques in agricultural sector particularly in crop management.

I. INTRODUCTION

As the worldwide populace has been consistently expanding (Kitzes et al., 2008), an extensive increment on food production must be accomplished (FAO, 2009), keeping up in the meantime accessibility and high wholesome quality over the globe, ensuring the natural ecosystems by utilizing feasible cultivating methods. To address these difficulties, the mind boggling, multivariate and erratic agricultural environments should be better comprehended by checking, estimating and dissecting consistently different physical angles and wonders. This infers investigation of enormous agrarian information (Kamilaris et al., 2017b), and the utilization of new data and correspondence advancements (ICT) (Kamilaris et al., 2016), both for short scale crop/ranch the executives just as for bigger scale biological systems' perception, improving the current errands of the executives and choice/arrangement making by setting, circumstance and area mindfulness. Bigger scale perception is encouraged by remote detecting (Bastiaanssen et al., 2000), performed by methods for satellites, planes and unmanned elevated vehicles (UAV) (for example rambles), giving wide-see depictions of the rural situations. It has a few favorable circumstances when connected to farming, being a notable, non-ruinous technique to gather data about earth highlights while information might be acquired efficiently over extensive topographical regions.

II. DEEP LEARNING IN CROP MANAGEMENT

Deep learning alludes to the utilization of counterfeit neural system models that contain a very huge number of handling layers, rather than "swallower" designs of increasingly conventional neural system philosophies. The presentation of these profound learning systems into horticulture (e.g., Carranza-Rojas et al., 2017), and specifically in the field of plant sickness finding (Yang and Guo, 2017), has just started to happen over the most recent few years, and to a somewhat restricted degree. The essential profound learning instrument utilized in this work is Convolutional Neural Networks (CNNs) (LeCun et al., 1998). CNNs comprise a standout amongst the most dominant systems for demonstrating complex procedures and performing design acknowledgment in applications with vast measure of information, similar to the one of example acknowledgment in pictures. The various applications of deep learning in crop management are discussed in following section.

Crop Identification

Lee et al. (2015) exhibited a CNNs framework for the mechanized acknowledgment of plants, in view of leaves pictures. Grinblat et al. (2016) built up a generally basic, however amazing neural system for the effective recognizable proof of three distinctive vegetable species dependent on the morphological examples of leaves' veins. All the more as of late, Pawara et al. (2017) looked at the execution of some regular example acknowledgment procedures with that of CNN models, in plants recognizable proof, utilizing three unique databases of (a fairly predetermined number of) pictures of either whole plants and organic products, or plant leaves, reasoning that CNNs radically beat traditional techniques. At long last, Fuentes et al. (2017) created CNN models for the location of 9 diverse tomato maladies and nuisances, with agreeable execution.

Yield Prediction

Yield expectation is a standout amongst the most vital and prominent points in exactness agribusiness as it characterizes yield mapping and estimation, coordinating of harvest supply with interest, and yield the executives. Best in class approaches have gone a long way past basic forecast dependent onthe chronicled information, yet consolidate PC vision advances to give information in a hurry and far reaching multidimensional examination of harvests, climate, and financial conditions to benefit as much as possible from the yield for ranchers and populace.

In recent years extraordinary ML strategies have been executed to accomplish precise yield forecast for various harvests (Subhadra et al., 2016). The best ML strategies have been Artificial Neural Networks (Drummond et al., 2003), Support Vector Regression (Ruß, 2009), M5-Prime Regression Trees (Ruß and Kruse, 2010;) and k-closest neighbor (Zhang et al., 2010).

Gonzalez-Sanchez et al. (2014) exhibited a similar investigation of ANN, SVR, M5-Prime, kNN ML systems and Multiple Linear Regression for harvest yield expectation in ten harvest datasets. To approve the models they utilized four exactness measurements: Root Mean Square Error (RMS), Root Relative Square Error (RRSE), Normalized Mean Absolute Error (MAE) and Correlation Factor (R). Results demonstrated that M5-Prime accomplished the most minimal mistakes over the delivered harvest yield models.

In another investigation Nari and Yang-Won (2016) connected four ML strategies, SVM, Random Forest (RF), Extremely Randomized Trees (ERT) and Deep Learning (DL) to assess corn yield in Iowa State. Examinations of the approval measurements demonstrated that DL gave increasingly stable outcomes by conquering the overfitting issue. Panda et al. (2010) actualized Back-spread Neural Network (BPNN) demonstrating to test the productivity of the accompanying four otherworldly vegetation files: NDVI, green vegetation file (GVI), soil balanced vegetation record (SAVI) and opposite vegetation list (PVI) in corn crop yield expectation. The outcomes demonstrated that the corn yield was best anticipated utilizing BPNN models that utilized the methods and standard deviations of PVI network pictures.

Crop Quality

The precise location and characterization of harvest quality attributes can build item cost and lessen squander. In correlation with the human specialists, machines can utilize apparently inane information and interconnections to uncover new characteristics assuming job in the general nature of the harvests and to recognize them.

Remote sensing, for example, satellite and airborne multi-ghastly filtering, photography and video, empowers exactness weed the executives through the age of opportune and precise weed maps (Lamb and Brown, 2001). Warm remote detecting through airborne warm symbolism can possibly distinguish spatial varieties in harvest water status (Tilling et al., 2006), which can empower enhancements in the water the executives in flooded trimming frameworks.

Remote sensing at noticeable and close infrared wavelengths (vis-NIR) has been utilized to devise numerous ghastly records for assessing diverse vegetation properties. This incorporates the measure of chlorophylls and other photosynthetic/photoprotective shades and the leaf territory list (LAI) (Barati et al., 2011 Haboudane et al., 2004; Zarco-Tejada et al., 2012). In excess of 100 vegetation lists alongside their appropriateness, representativeness, condition and usage exactness have as of late been evaluated by Xue and Su (2017).

Disease Detection

Both in outside and nursery conditions, the most broadly utilized practice in irritation and ailment control is to consistently splash pesticides over the trimming region. To be compelling, this methodology requires critical measures of pesticides which results in a high budgetary and noteworthy ecological expense. ML is utilized as a piece of the general accuracy farming administration, where agro-synthetic substances input is focused as far as time, place and influenced plants. Carranza-Rojas et al. created convolutional neural system models to perform plant ailment discovery and finding utilizing straightforward leaves pictures of solid and ailing plants, through profound learning strategies. Preparing of the models was performed with the utilization of an open database of 87,848 pictures, containing 25 unique plants in a lot of 58 unmistakable classes of [plant, disease] blends, including solid plants. A few model structures were prepared, with the best execution achieving a 99.53% achievement rate in recognizing the relating [plant, disease] mix (or sound plant). Explicit CNN designs were prepared and evaluated, to frame a computerized plant malady identification and conclusion framework, in view of straightforward pictures of leaves of sound and ailing plants. The accessible dataset contained pictures caught in both exploratory (research facility) setups and genuine development conditions in the field. The proposed profound learning approach may discover more broad arrangements than shallow methodologies, which learn with less information yet are explicit to few yields (e.g., Pantazi et al., 2016). Examination of the models depended on their execution on the testing set (all models accomplished 100% precision on the preparation set).

Plant illness determination through optical perception of the manifestations on plant leaves, joins an altogether high level of multifaceted nature. Because of this multifaceted nature and to the substantial number of developed plants and their current phytopathological issues, even experienced agronomists and plant pathologists regularly neglect to effectively analyse explicit ailments, and are therefore prompted mixed up ends and medicines. The presence of a computerized computational framework for the discovery and conclusion of plant sicknesses, would offer a profitable help to the agronomist who is approached to perform such judgments through optical perception of leaves of contaminated plants (Mohanty et al., 2016; Yang and Guo, 2017). Mohanty et al. (2016) thought about two surely understood and built up structures of CNNs in the distinguishing proof of 26 plant ailments, utilizing an open database of leaves pictures of 14 distinct plants. Their outcomes were extremely encouraging, with progress rates in the computerized distinguishing proof up to 99.35%. Nonetheless, a principle disadvantage was that the whole photographic material included exclusively pictures in exploratory (research center) setups, not in genuine conditions in the development field. Sladojevic et al. (2016) built up a comparative procedure for plant infection location through leaves pictures utilizing a comparative measure of information accessible on the Internet, which incorporated fewer maladies (13) and diverse plants (5). Achievement rates of their models were somewhere in the range of 91% and 98%, contingent upon the testing information.

Weed Detection

Aside from ailments, weeds are the most vital dangers to edit generation. The most concerning issue in weeds battling is that they are hard to distinguish and separate from yields. PC vision and ML calculations can improve discovery and separation of weeds requiring little to no effort and with no natural issues and symptoms. In future, these advances will drive robots that will pulverize weeds, limiting the requirement for herbicides. Machine vision innovation can give essential instruments to continuous picture handling and weed identification (Behmann et al., 2015; dos Santos Ferreira et al., 2017; Yang et al., 2000). It might be utilized related to brilliant sprayers to encourage exactness herbicide application (Berge et al., 2012). Different ground-based weed acknowledgment procedures including counterfeit neural system (Liakos et al., 2018), fluorescence imaging (Longchamps et al., 2010), and unearthly detecting (Pantazi et al., 2016) have been contemplated for site-explicit weed the executives in arable yields (Behmann et al., 2015; do Santos Ferreira et al., 2017; Yang et al., 2000).

III. CONCLUSION

This study would persuade more analysts to explore different avenues regarding profound picking up, applying it for taking care of different horticultural issues including arrangement or expectation, identified with PC vision and picture examination, or all the more for the most part to information investigation. The general advantages of profound learning are empowering for its further use towards more astute, progressively economical cultivating and increasingly secure sustenance generation.Detecting advances and ML procedures are quickly progressed amid the most recent decade. These improvements are probably going to keep giving practical and increasingly exhaustive datasets joined with progressively refined algorithmic arrangements empowering better harvest and condition state estimation and basic leadership. We are toward the start of a promising way that can possibly altogether change crop yield the board.

REFERENCES

[1] Barati, S., Rayegani, B., Saati, M., Sharifi, A., Nasri, M., 2011. Comparison the accuraciesof different spectral indices for estimation of vegetation cover fraction in sparse vegetated areas. Egypt. J. Remote Sens. Space Sci. 14, 49–56.
[2] Behmann, J., Mahlein, A.K., Rumpf, T., Römer, C., Plümer, L., 2015. A review of advanced machine learning methods for the detection of biotic stress in precision cropprotection. Precis. Agri. 16, 239–260. https://doi.org/10.1007/s11119-014-9372-7.
[3] Berge, T., Goldberg, S., Kaspersen, K., Netland, J., 2012. Towards machine vision basedsite- specific weed management in cereals. Comput. Electron. Agr. 81, 79–86.
[4] Carranza-Rojas, J., Goeau, H., Bonnet, P., Mata-Montero, E., Joly, A., 2017. Going deeperin the automated identification of Herbarium specimens. BMC Evol. Biol. http://dx.doi.org/10.1186/s12862-017-1014-z.
[5] dos Santos Ferreira, A., Freitas, D.M., da Silva, G.G., Pistori, H., Folhes, M.T., 2017. Weeddetection in soybean crops using ConvNets. Comput. Electron. Agr. 143, 314–324.https://doi.org/10.1016/j.compag.2017.10.027.
[6] Drummond, S.T., Sudduth, K.A., Joshi, A., Birrel, S.J., Kitchen, N.R., 2003. Statistical and neural methods for site-specific yield prediction. Trans. Am. Soc. Agric. Eng. 46,5–14.
[7] Gonzalez-Sanchez, A., Frausto-Solis, J., Ojeda-Bustamante, W., 2014. Predictive ability ofmachine learning methods for massive crop yield prediction. Spanish J. Agric. Res.12, 313–328.
[8] Lamb, D.W., Brown, R.B., 2001. PA—Precision agriculture. J. Agric. Eng. Res. 78,117–125.
[9] LeCun, Y., Bottou, L., Bengio, Y., Haffner, P., 1998. Gradient-based learning applied todocument recognition. Proc. IEEE 86 (11), 2278–2324.
[10] Lee, S.H., Chan, C.S., Wilkin, P., Remagnino, P. 2015. Deep-plant: Plant identificationwith convolutional neural networks. 2015 IEEE Intl Conf. on Image Processing, pp.452–456.
[11] Liakos, K., Busato, P., Moshou, D., Pearson, S., Bochtis, D., 2018. Machine learning in agriculture: a review. Sensors 18, 2674. https://doi.org/10.3390/s18082674.
[12] Longchamps, L., Panneton, B., Samson, G., Leroux, G.D., Thériault, R., 2010.Discrimination of corn, grasses and dicot weeds by their UV-induce d fluorescencespectral signature. Precis. Agric. 11, 181–197. https://doi.org/10.1007/s11119-009-9126-0.
[13] Fuentes, A., Yoon, S., Kim, S.C., Park, D.S., 2017. A robust deep-learning-based detectorfor real-time tomato plant diseases and pest recognition. Sensors 17, 2022. http://dx.doi.org/10.3390/s17092022.
[14] Food and Agriculture Organization of the United Nations, 2009. How to Feed the World in 2050., Rome: s.n.
[15] Grinblat, G.L., Uzal, L.C., Larese, M.G., Granitto, P.M., 2016. Deep learning for plant identification using vein morphological patterns. Comput. Electron. Agric. 127,418–424.
[16] Haboudane, D., Miller, J.R., Pattey, E., Zarco-Tejada, P.J., Strachan, I.B., 2004.Hyperspectral vegetation indices and novel algorithms for predicting green LAI ofcrop canopies: Modeling and validation in the context of precision agriculture. Remote Sens. Environ. 90, 337–352.
[17] Konstantinos P. Ferentinos, Deep learning models for plant disease detection and diagnosis, Computers and Electronics in Agriculture 145 (2018) 311–318.
[18] Mohanty, S.P., Hughes, D.P., Salathé, M., 2016. Using deep learning for image-basedplant disease detection. Front. Plant Sci. 7http://dx.doi.org/10.3389/fpls.2016.01419.Article: 1419.
[19] Panda, S.S., Ames, D.P., Panigrahi, S., 2010. Application of vegetation indices for agricultural crop yield prediction using neural network techniques. Remote Sens. 2,673–696.
[20] Pantazi, X.E., Moshou, D., Tamouridou, A.A., Kasderidis, S. 2016. Leaf disease recognitionin vine plants based on local binary patterns and one class

support vector machines.12th IFIP International Conference on Artificial Intelligence Applications andInnovations (AIAI 2016), Sept. 16–18, Thessaloniki Greece, Proceedings, Springer,pp. 319–327.

[21] Pawara, P., Okafor, E., Surinta, O., Schomaker, L., Wiering, M. 2017. Comparing localdescriptors and bags of visual words to deep convolutional neural networks for plantrecognition. 6th Intl Conf. on Pattern Recognition Applications and Methods(ICPRAM 2017).

[22] Ruß, G., 2009. Data mining of agricultural yield data: a comparison of regression models.In: Perner, P. (Ed.), Advances in Data Mining. Applications and Theoretical Aspects:9th Industrial Conference, ICDM 2009, Leipzig, Germany, July 20 - 22, 2009.Proceedings. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 24–37.

[23] Ruß, G., Kruse, R., 2010. Feature Selection for Wheat Yield Prediction. In: Bramer, M.,Ellis, R., Petridis, M. (Eds.), Research and Development in Intelligent Systems XXVI:Incorporating Applications and Innovations in Intelligent Systems XVII. Springer,London, London,pp. 465–478.

[24] Yang, X., Guo, T., 2017. Machine learning in plant disease research. Europ. J. BioMed. Res. 6–9. http://dx.doi.org/10.18088/ejbmr.3.1.2016.pp6-9.

[25] Yang, C., Prasher, S.O., Landry, J., DiTommaso, A., 2000. Application of artificial neuralnetworks in image recognition and classification of crop and weeds. Can. Agri. Eng.42, 147–152.

[26] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., Stefanovic, D., 2016. Deep neuralnetworks based recognition of plant diseases by leaf image classification. Computat. Intelligence Neurosci. http://dx.doi.org/10.1155/2016/3289801. Article ID:3289801.

[27] Subhadra, M., Debahuti, M., Gour Hari, S., 2016. Applications of Machine LearningTechniques in Agricultural Crop Production: A Review Paper. Indian J. Sci.Technol. 9.

[28] Tilling, A.K., O'Leary, G.J., Ferwerda, J.G., Jones, S.D., Fitzgerald, G.J., Rodriguez, D.,Belford, R., 2006. Remote sensing of nitrogen and water stress in wheat. Field CropsRes. 104, 77–85.

[29] Xue, J., Su, B., 2017. Significant remote sensing vegetation indices: a review of developmentsand applications. J. Sens. 2017, 17.

[30] Yang, J., Gong, W., Shi, S., Du, L., Sun, J., Song, S., 2016. Laser-induced fluorescencecharacteristics of vegetation by a new excitation wavelength. Spectrosc. Lett. 49,263–267.

[31] Zarco-Tejada, P.J., González-Dugo, V., Berni, J.A.J., 2012. Fluorescence, temperature andnarrow-band indices acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera. Remote Sens. Environ. 117,322–337.

[32] Zhang, L., Zhang, J., Kyei-Boahen, S., Zhang, M., 2010. Simulation and prediction ofsoybean growth and development under field conditions. Am.-Eurasian J. Agric.Environ. Sci. 7, 374–385.

