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Applications of Deep Learning Techniques in Agriculture : A Review

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Abstract: *Agriculture is one of the major industries in the world. With promising results and enormous capability, deep learning technology has attracted more and more attention to both theoretical research and applications for a variety of image processing and computer vision tasks. In this paper, the author investigate research contributions that apply deep learning techniques and ML to the agriculture domain. Different types of deep neural network architectures and ML techniques in agriculture are surveyed and the current state-of-the-art methods are summarized. The main objective of this paper is to find the various applications of Deep learning in agriculture such as for irrigation, weeding, Pattern recognition, crop disease identification etc. The paper reviews the specific employed deep learning models, the source of the data, the performance of each study, the employed hardware and the possibility of real-time application to study eventual integration with autonomous robotic platforms. The survey shows that deep learning-based research has superior performance in terms of accuracy, which is beyond the standard machine learning techniques nowadays.*

Keywords: Deep learning, agricultural robots, crop management, artificial intelligence, precision livestock farming

I. INTRODUCTION

With the increase in the global population, there has also been a huge increase in the demand of food and agricultural products. To meet this increasing demand, an equivalent increase in the agricultural production is required, without comprising the quality of food products and also without affecting the natural environment. An important research area in this domain is Image acquisition and analysis. Using images of agricultural fields and parts of plants, important aspects of the field and plants can be explored. With the automatic image analysis of the field, the quality of soil can be examined and effective measures can be taken to make the soil fertilize and suitable for crops production[2]. Similarly, the diseases in plants can be detected and essential steps can be taken well in time to improve the quality of crops and reduce the health risks to humans from the diseased crops. Agricultural crops are prone to pests, which have threats of health problems to people [1] .

Emerging ICT technologies relevant to the understanding of agricultural ecosystems include remote sensing , the Internet of Things, cloud computing, and the analysis of big data. Remote sensing provides large-scale snapshots of the agricultural environment by means of satellites, planes and unmanned aerial vehicles (UAVs, i.e. drones).When applied to agriculture it has several advantages, being a well-known, non-destructive method of gathering information on earth features. Remote sensing data can be collected on very large geographic areas, including inaccessible areas. The IoT uses state-of - the-art sensor technology to measure various parameters in the field, while cloud computing is used to collect, store, pre-process and model huge amounts of data from different, heterogeneous sources. Eventually, big data processing is used in conjunction with cloud computing to analyze the data stored in the cloud on a large scale in real time. A large sub-set of the data collected by remote sensing, and the IoT contains images. Images can provide a complete picture of agricultural fields and a number of problems could be solved through image analysis. Therefore, image analysis is an important area of research in the agricultural domain and intelligent inspection techniques are used to identify / classify pictures, recognize abnormalities, etc., in different agricultural applications [13].

Machine learning combined with high-performance computing guarantees the ability to process large amounts of image data effectively. Early solutions to computer vision tasks depended on traditional machine learning methods, i.e., feature-based manual method. Common features include Deformable Part-Based Model (DPM),Histogram of Oriented

Gradient (HOG)] and Scales-Invariant Feature Transformation (SIFT) ,Speeded Up Robust Features (SURF) and Haar-like features . They were usually combined with classifiers such as Support Vector Machine (SVM) to classify each image pixel. Although the traditional methods are easy to understand and many improvements have been done to them, most of the mare verified in low and medium density images and they usually need to be changed according to the specific situations . Moreover, most traditional methods either ignore the problems in dense scenes, namely, there is no discussion on dense scenes, or use simple heuristic methods based on shape and size, these methods are very in effective in natural environments with severe occlusion and large scale changes. Therefore, traditional machine learning methods are not appropriate for dense images. It has been demonstrated that in many applications, features extracted by deep learning are more effective than these hand-crafted feature. Moreover, deep learning solves various challenges in dense images. Deep Learning (DL) belongs to machine learning, based on representation learning of data, which realizes artificial intelligence by means of artificial neural networks with many hidden layers and massive training data. DL has been successful in computer vision , natural language processing, bioinformatics , automatic control , machine translation , automatic driving and other practical problems . The reason for the success of DL lies in its unique characteristics of network structure: deep neural network can acquire high-level features by learning local features from the bottom and then synthesizing these features at the top. DL uses multi-level abstraction to learn complex feature representations from raw data and generate components automatically. Different features at different levels can correspond to different tasks. Deep learning is a technology that uses deep network structure to learn features. Deep learning emphasizes the depth of the model structure, highlights the importance of feature learning and proposes various techniques to learn more and higher-level features better and faster. Strong learning ability enables them to implement various kinds of problems especially well and flexibly adapt to numerous highly complex problems. Monitoring and studying a large number of interesting objects in videos or images is an important task for the macro-world and micro-field, for instance, the research on crowding traffic and microscopic microorganisms. Usually, advances in one area are driven more by some combination of expertise, resources, and application requirements in other areas . Similarly, applications of DL in analyzing dense scenes spread to the agricultural sector after advances in medical diagnostics and population analysis. More and more scenes in agriculture produce a lot of high-density images, and they are becoming more and more attention. At present, agricultural tasks have been transformed into tasks of agro vision (computer vision in agriculture). There have been some reviews on the applications of DL in agriculture and some reviews pertinent to the use of DL in computer vision. They either gave a comprehensive overview of DL methods applied throughout the agricultural field or the latest research of DL technology in a certain agricultural field and also reviewed the application of DL methods in general computer vision tasks. However, none of them involved how DL works in dense agricultural scenes. The use of DL in fruit detection and yield estimation is summarized, including the problem of occluded fruit in imaging and the solutions. However, they were only concerned with the detectionand yield estimates while ignoring other agricultural tasks containing a large number of objects. Thus, the motivation for preparing this review stems from the need to summarize the applications of DL in agriculture with the increase of dense scenes and images[14].This paper investigates the applications and techniques of DL in agriculture. This paper aims to provide a reference to the DL methods for agricultural researchers. This paper can be helpful for researchers to retrieve the literatures related to the research problems quickly and accurately. This study is divided into five sections. Section 1 introduces the concept of deep learning in agriculture, Section 2 explains the methodology used in the present study of this article, Section 3 presents review of existing literature, Section 4 discusses Applications of Deep Learning in Agriculture in detail and Section 5 presents the conclusions of the work.

II. METHODOLOGY

In this study, the first step was citation databases analyse, it involved two steps:

- Collection of related works and,
- Detailed review and analysis of the works.

A survey is performed on various research papers on Applications of deep learning in agriculture. For this review paper, multiple sources have been used. Scopus has been used for searching various papers on the topic with the Boolean “Deep Learning and Agriculture. From Mendeley, the abstracts of the papers were studied and those which were found useful for this review, their full papers were downloaded from Scopus, Google Scholar, and Research Gate. The research paper from 2010-2021 selected for study. In the first step, a keyword-based search using all combinations of two groups of keywords of which the first group addresses deep learning and the second group refers to application of deep learning in farming.

III. LITERATURE REVIEW

In [16] proposed a Agri-IoT framework, a semantic framework for IoT based smart farming applications, which supports reasoning over various heterogeneous sensor data streams in real-time. Agri IoT can integrate multiple cross-domain data streams, providing a complete semantic processing pipeline, offering a common framework for smart farming applications. Agri-IoT supports large-scale data analytics and event detection, ensuring seamless interoperability among sensors, services, processes, operations, farmers and other relevant actors, including online information sources and linked open datasets and streams available on the Web.[17] did comprehensive review of research dedicated to applications of deep 9 learning for precision agriculture is presented along with real time applications, 10 tools and available datasets. The findings exhibit the high potential of applying deep 11 learning techniques for precision agriculture. In this paper the role of Smart farming for sustainable agriculture is discussed,a novel approach to fruit production prediction using deep neural networks to build a fast and reliable prediction system for agricultural production is presented. In this article, authors have considered different types of fruit production data (apples, bananas, citrus, pears, grapes, and total fruits), analysed this data, and predicted the future production of these fruits using deep neural networks. The data are taken from the National Bureau of Statistics of Pakistan and the production output of major fruits. Authors have implemented 3 different methods to predict the data for future fruit production. The first method is Levenberg-Marquardt optimization (LM), which was 65.6% accurate; the second method is called scale conjugate gradient back propagation (SCG), which had an accuracy of 70.2%, and the third method, is Bayesian regularization back propagation (BR), which was 76.3% accurate. Incorporates the performance analysis of clustering algorithms when applied to FAO Soya bean dataset. The algorithms are compared on the basis of various parameters, such as time taken for completion, number of iterations, and number of clusters formed and the complexity of the algorithms. Finally, based on the analysis, the paper determines the best befitting algorithm for the FAO Soya bean dataset. Comprehensive review of research dedicated to applications of machine learning in agricultural production systems is performed. The works analyzed were categorized in (a) crop management ; (b) livestock management; (c) water management; and (d) soil management. The survey shows that deep learning-based research has superior performance in terms of accuracy, which is beyond the standard machine learning techniques nowadays.

In [18] examine the ability of deep learning methods for remote sensing image classification for agriculture applications. FCN8s model achieved 75.1% accuracy on detecting weeds compared to 66.72% of U-net using 60 training images. However, the U-net model performed better on detecting crops which is 60.48% compared to 47.86% of FCN-8s.[19] presented a comprehensive analysis of important metrics in practical applications: accuracy, memory footprint, parameters, operations count, inference time and power consumption. Key findings are: (1) power consumption is independent of batch size and architecture; (2) accuracy and inference time are in a hyperbolic relationship; (3) energy constraint is an upper bound on the maximum achievable accuracy and model complexity; (4) the number of operations is a reliable estimate of the inference time. [20] proposed a deep learning-based approach that automates the process of classifying banana leaves diseases. Deep learning based classification framework for remotely sensed time series is developed. For the challenging task of classifying summer crops using Lands at Enhanced Vegetation Index (EVI) time series, two types of deep learning models were designed: one is based on Long Short-Term Memory (LSTM), and the other is based on one-dimensional convolutional (Conv1D) layers. The highest accuracy (85.54%) and F1 score (0.73) were achieved by the Conv1D-based model. The banana harvest data is used from agrarian reform beneficiary (ARB) cooperative in Davao del Norte, Philippines. In this study RNN-LSTM outperforms the ARIMA model with 32.31 percent reduction in error rates.

A simulated deep convolutional neural network for yield estimation is presented. Knowing the exact number of fruits, flowers, and trees helps farmers to make better decisions on cultivation practices, plant disease prevention, and the size of harvest labor force. To count the number of fruits on a coffee branch by using information from digital images of a single side of the branch and its growing fruits is proposed. The use of a state-of-the-art object detection framework, Faster R-CNN, in the context of fruit detection in orchards, including mangoes, almonds and apples is presented. A Convolutional Neural Network (CNN) architecture to classify the type of plants from the image sequences collected from smart agro-stations is proposed. A model is to deliver direct advisory services to even the smallest farmer at the level of his/her smallest plot of crop, using the most accessible technologies using deep learning is proposed. It is a recommender model built using a classifier and an optimization of the classifier. This work proposed MDNN where the weight matrices are calculated with L2 regularization and PSO utilized to tune the hyper parameters of MDNN and its network structure to improve the prediction accuracy[15].

A study explains the harvesting in date fruit orchard using robotics and Deep Learning mechanism. There are two pre-learning CNN mechanisms; namely, AlexNet and VGG-16. The suggested method accomplish extremely good classification based on the difficult dataset with matching ration. A study has planned a correct and strong algorithm for a new mechanism to critically find the growth of cucumber using robotic harvesting automated process in agriculture. This algorithm is a different sort of implementations and mining methodologies of existing data to gain of cucumber field with extraordinary components[22].

In following subsection the author classified 5 agricultural domains namely Plant disease identification, identification of weeds, plant recognition, fruits counting and crop type classification. For this purpose an intensive review of deep neural network efforts in the agriculture domain is performed.

3.1 Yield Prediction

In [33] yield prediction is the most essential aspect of proper agriculture. Some studies have been discussed regarding yield prediction. The authors proposed a model which is an RNN DL algorithm called DRQN over the Q-Learning RL algorithm to determine the crop yield. The main goal of this work was to reduce the error and increase the forecast accuracy, resulting in better food production. In another study of yield prediction, the authors of in a paper used a DL methodology of yield prediction to develop a model for wheat and barley crops based on NDVI and RGB data acquired from UAVs. The main aim of the model was to improve performance and provide accurate yield estimation using RGB images. In a paper , the authors use the field images to develop a DCNN framework for automatically recognizing and classifying several biotic and abiotic paddy crop stressors the pre-trained VGG16 CNN model gained an average accuracy of 92.89%. In another study, the authors proposed a DL framework to predict the yield basis on environmental data and optimization techniques that use CNNs and RNNs. To predict yields for both corn and soybean this model achieved an RMSE of 9% and 8% of their average yields, respectively. A DNN model, CNN, and LSTM are proposed for soybean crop yield prediction by the authors of a study . In this study, the RMSE is 0.81 and the % error is 2.70. The authors of in an article proposed a model that fuses two BPNNs with an IndRNN which is called BBI-model. This model can make accurate predictions in different seasons. In another study of yield prediction, the authors of a paper proposed a DNN based model is used to predict yield. In a paper , the authors developed a combined model which includes CNN and LSTM to predict yield. This model performed well, with an RMSE of 8.24%. Also, in the next work, the authors developed a model Using CNN and LSTM networks. They trained CNN-LSTM, convolutional LSTM, and 3D-CNN architectures with the captured images. With the 3D-CNN model, they have achieved 218.9 kg/ha MAE and 5.51% MAPE. The authors in this paper developed a DNN-based model for crop selection and yield prediction. This model aims to get better output and prediction. Other studies in yield prediction are [38], [39], [40]in [34][20] in [15] and [46]in [45].

3.2 Disease Detection

Crop diseases constitute a major threat in agricultural production systems that deteriorate yield quality and quantity at production, storage, and transportation level. At farm level, reports on yield losses, due to plant diseases, are very common [48]. Furthermore, crop diseases pose significant risks to food security at a global scale. Timely identification of plant diseases is a key aspect for efficient management. In the past few years, computer vision, especially by employing deep learning, has made remarkable progress[47].

DL methods can reduce the problems to a manageable level. The authors are presented with pre-trained models like VGG19 for classifying diseases such as early blight, late blight, and healthy in potato leaves. They have achieved 97.8% accuracy. In a paper the authors identify tomato leaves diseases using CNN; AlexNet and VGG16; GoogLeNet and ResNet; ResNet and the SGD optimization and achieved 99.84% , 97.49%, 97.49%, 97.28% and 99% accuracy respectively. Detect wheat crop diseases using CNN because it has automatically extract features by processing the raw images directly. Their proposed method obtained 84.54% accuracy. The authors developed models to detect nitrogen stressed, and yellow rust infected and healthy winter wheat canopies based on hierarchical self-organizing classifier and hyper spectral reflectance imaging data. They used models like ANN models and spectral reflectance features ; self-organising map (SOM) neural network and data fusion of hyper-spectral reflection and multi-spectral fluorescence imaging. These studies aimed at the accurate detection of categories for a more effective usage of fungicides and fertilizers according to the plant's needs; precise targeting of pesticides in the field; accurate detection, before it can visibly detected, of yellow rust infected winter wheat cultivar "Madrigal"; and accurate discrimination between the plant stress, which is caused by disease and nutrient deficiency stress under field conditions respectively. In another study presented a CNN-based method for the disease detection diagnosis based on simple leaves images with sufficient accuracy to classify between healthy and diseased leaves in various plants[34].In [34] the work discussed are : CNN and MCNN model adopted for detecting diseased leaves in the Mango plant with accuracies 96.67% and 97.13% respectively. In a study the authors detect apple leaves diseases like apple black rot, apple cedar apple rust, healthy apple, and apple scab with their proposed model CNN and they achieved 98.54% accuracy. CNN model is developed based on a Lenet architecture for soybean plant disease recognition and classification. This model performed well and achieved a 99.32% accuracy. In the next paper, a DCNN was designed to operate symptom-wise recognition of cucumber diseases by authors. This model had a significant recognition result, with an accuracy of 93.4%. The authors of [155], proposed a slightly modified CNN model named LeNet. This model was mainly used to detect and identify diseases in tomato leaves using the simplest approach. This model has achieved an average accuracy of 94-95%. The authors in an article , developed a DL system with VGG16 architecture to detect rice plant diseases. Due to the small dataset, the accuracy of the detection was not high enough. This model only achieved a 60% test accuracy. In a paper the authors proposed GoogLeNet and Cifar10 models based on DL are proposed for leaf disease recognition. This model aims to enhance maize leaf disease recognition accuracy and reduce the number of network parameters. The GoogLeNet and Cifar10 models achieved an average accuracy of 98.9%, and 98.8% respectively. A DCNN based method proposed to identify rice diseases. Images of diseased and healthy rice leaves and stems were collected from the rice experimental field to make the dataset. This proposed model has achieved 95.48% of accuracy. a weakly supervised DL framework was proposed by the authors for the recognition and identification of wheat diseases. Two different architectures that are VGG-FCN-VD16 and VGG-FCN-S was implemented to train the dataset. The system achieved the recognition accuracy of 97.95% and 95.12% respectively. Paddy is one of the most important crops all over the world. Lots of farmers are not aware of paddy leaf disease. Here, in [33] studies have been introduced on the application of DL to detect and classify paddy leaf diseases.

3.3 Weed Detection

In [33] four studies have been introduced on the application of DL to the detection of agricultural weeds. In a paper, the authors use the inception model (V2) to the detecting of weeds in crops. Their approach model can detect weed with 98% of accuracy. In a study , the authors detect weed on broad-leaf using CNN algorithms with 96.88% accuracy. Ina paper, the authors proposed a new model using R-FCN with ResNet-101. They also compare their proposed model with Faster R-CNN and R-FCN. Their model gets an overall better result than Faster R-CNN and R-FCN with 81% of accuracy detecting farmland weed. The authors in paper employ the DCNN method to estimate the growth stage of several weed species in terms of the number of leaves with 70%overall accuracy and 96% accuracy while accepting a two-leaf variance. More studies on detection of agricultural weeds are in [34], [58], [59] and [60].

3.4 Species Recognition

In species recognition the main goal is the automatic identification and classification of plant species in order to avoid the use of human experts, as well as to reduce the classification time. A method for the identification and classification of three legume species, namely, white beans, red beans, and soybean, via leaf vein patterns has been presented. Vein morphology carries accurate information about the properties ofthe leaf. It is an ideal tool for plant identification in comparison with color and shape[34].

3.5 Soil Management

In Soil Management ML is used in prediction-identification of agricultural soil properties, such as the estimation of soil drying, condition, temperature, and moisture content. The first study for soil management is the work of [41]. More specifically, this study presented a method for the evaluation of soil drying for agricultural planning. The method accurately evaluates the soil drying, with evapotranspiration and precipitation data. The goal of this method was the provision of remote agricultural management decisions. The second study [42] was developed for the prediction of soil condition. In particular, the study presented the comparison of four regression models for the prediction of soil organic carbon (OC), moisture content(MC), and total nitrogen (TN). In a third study [43], the authors developed a new method based on a self adaptive evolutionary-extreme learning machine (SaE-ELM) model and daily weather data. The aim was the accurate estimation of soil temperature for agricultural management. The last study [44] presented a novel method for the estimation of soil moisture, based on ANN models using data from force sensors on ano-till chisel opener[34].

IV. APPLICATIONS OF DEEP LEARNING IN AGRICULTURE

This section describes the survey papers related with applications of deep learning in agriculture.

4.1 Plant Domain

With the development of agricultural modernization, the area of large-scale cultivation becomes increasing. DL has a wide range of applications in the planting of agriculture. There are several works on DL applying to crop disease classification or detection. The work by Ha et al. [42] proposed a highly accurate system to detect radish disease (Fusarium wilt). The radish was classified into diseased and healthy through the deep convolutional neural network (DCNN). Thework by Ma et al. [43] developed a DCNN to recognize cucumber four types of cucumber diseases. Compared to conventional methods (e.g., RF, SVM, and AlexNet), DCNN can detect better cucumber diseases with 93.41% of accuracy. Similar to the research [50] in [49], Lu et al. [51] in [49],[3] and [3] in [1] came up with CNNs to identify types of rice diseases with more than 95% of accuracy, which demonstrated the superiority of CNN based models in identifying rice diseases. The work by Liu et al. [52] in [49] presented a novel AlexNet-based model to detect four types of common apple leaf diseases. The approach demonstrated97.6% and improved the robustness of the CNN model in experiment. Considering the food security issues, Mohanty et al. [53]in [49] proposed to identify 26 types of diseases and14 crop species using the CNN model. The model demonstrated an excellent performance, which proved itself was feasible and robust for detection diseases. In their work[6], the authors have contributed towards the automatic recognition of plant diseases using image analysis. They have used GoogleNetBN and compared the results with VGG16 having 16layers and Inception V3 with 48 layers with accuracy 95.48%. In another work[4], S.Gayathri et al. proposed CNN LeNet model for recognition of four tea leaf diseases – blister blight, red scab, red leaf spot and leaf blight. In their work of 2020[5], the authors have used ResNet50 model to detect 5 strawberry diseases from “Taoyuan No. 1” and “Xiang-Shui” strawberry cultivars in Miaoli County, Taiwan [1].The work by Fuentes et al. [48] in [49] used DL three meta-architectures, faster region-based convolutional neural network (Faster R-CNN), region-based fully convolutional network (R-FCN), and single shot multibox detector (SDD). The work showed that the developed models can effectively detect nine types of diseases and pests in complex surrounding. Other works in recognition of plant diseases are [7] [1],[20] in [15], [47] and [3] in [1].

Crop classification and identification are the critical initial stages of the agricultural monitoring system. Zhong et al. [50] presented a classification framework for identifying crop growth patterns and crop types using DL applied to time-series remotely sensed data based on Conv1-D. Their work showed that the framework was effective in representing the time series of multi-temporal classification tasks. Another study by Milioto et al. [51] presented a system to detect and classify sugar beets and weeds without standing performance. The work by Ghazi et al. [52] combined transfer learning and popular CNN architectures, including VGGNet, AlexNet, and GoogLeNet to recognize plant types. Their model placed the third inPlanCLEF2016. The work by Zhu et al. [53] used an improved inception V2 architecture to identify plant species. Through experiment with real scenes, it was proved that the proposed method had accuracy superior to Faster RCNN in identifying leaf species in a complex environment. In the study, to boost fruit production and quality, the work by Dias et al. [54] developed a robust system to recognize apple flowers using CNN. The problem addressed in many research papers was the recognition of medicinal plants and their uses. In 2019, Krishnaveni et al. [19] were able to classify 12 medicinal plants. In their work of 2019, Dileep et al.[20] proposed AyurLeaf CNN for classification of 40 medicinal plant species. AyurLeaf CNN was based on the CNN architecture AlexNet . A five-fold cross validation was used and the result was compared with AlexNet and DLeaf. Their accuracy was 96.76% which was greater than other models. Dudi et al. [21] used two modules for recognition of medicinal plants – a four layer CNN based feature extraction and machine learning based classification using ANN, SVM, Naïve Bayes and k-Nearest neighbor. More works on Crop classification and identification can be found in n [8], [9], Gokul et al. [10] [11],Adetiba et al. and Bargoti S. et al.[1].

Prediction of crop yield that can predict production in advance before harvest belongs to another area of study in planting. It provides forecast data based on region, crop, and multiple forecast surveys at different growth stages. To observe the growth of apple at every stage, Tian et al. [54] put forward aYOLOV3-dense model to detect apple growth and estimate yield using data augment technique to avoid over fitting. The orchard in their study involved undulating lighting, complex backgrounds, overlapping of fruits. Their approach was concluded as valid for real-time application in apple orchards. The work by Rahnemoonfar and Sheppard [55] used an improved Inception-ResNet model with accuracy for estimating fruit yield in terms of the number of fruits. The model was efficient even with complex condition on fruits.[49] A study on Agricultural Fruit Prediction Using Deep Neural Networks is performed [15].Deep learning is also used to track and predict various environmental impacts on crop yield such as weather changes. Convolutional Neural Networks (CNN) is the most widely used deep learning algorithm in these kind of studies, and the other widely used deep learning algorithms are Long-Short Term Memory (LSTM) and Deep Neural Networks (DNN). Mariannie Rebortera et al. performed a research on Forecasting Banana Harvest Yields using Deep Learning Deep learning techniques[1].

4.2 Animal Domain

As the concern on animals grows, DL technologies have been adopted in the animal domain for monitoring and improving animal breeding environment and the quality of meat products. The study on DL-based face recognition and behavior analysis of pigs and cows is very active in applied research. To develop an automatic recognition method of nursing interactions for animal farms by using DL techniques, it is showed that the fully convolutional network combining spatial and temporal information was able to detect nursing behaviors, which was tremendous progress in identifying nursing behaviors in pig farm. A Mask R-CNN architecture to settle cattle contour extraction and instance segmentation in a sophisticated feedlot surrounding is presented. DL techniques based on nose pattern characteristic to identify cattle to address the loss or exchange of animals and inaccurate insurance claim is used. Inspired by the work of face recognition, the work proposed a CNN-based model to recognize pigs. In order to predict sheep commercial value, an automatic system is built to recognize sheep types in a sheep environment and reached 95.8%accuracy. counting CNN to deal with the pig amounts and got 1.67MAE per image is proposed .Deep learning methods viz. CNN, RNN, LSTM can be used to provide accurate prediction and estimation of farming parameters to optimize the economic efficiency of livestock production systems, such as cattle and eggs production. A study on smart farming is key to developing sustainable agriculture is proposed[15].

4.3 Land Cover

Deep learning is also used in Land cover classification (LCC) is considered as a vital and challenging task in agriculture, and the key point is to recognize what class a typical piece of land is in. Deep learning methods such as CNN, GAN and RNN are able to be used for land cover classification of remote sensing image data. Deep learning applications in land use classification based on Sentinel-2 time series is explained. Agriculture Companies are leveraging computer vision and deep-learning algorithms to process data captured by drones and/or software-based technology to monitor crop and soil health [15]. Kussul et al. [56] presented a multi-level DL technique that classified crop types and land cover from Landsat-8 and Sentinel-1A RS satellite imagery with nineteen multi temporal scenes. Thework by Gaetano et al. [57] proposed a two-branch end-to-end model called MultiReso LCC. The model extracted characteristics of land covers and classified land covers by combing their attributes at the PAN resolution. The work by Scott et al. [58] train eda DCNNs model and used transfer learning and data augmentation to classify land covers for

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remote sensing imagery. The work by Xing et al. [59] used improved architectures, VGG16, ResNet-50, and AlexNet to validate land cover, and the results showed that the proposed method was effective with accuracy 83.80%. The work by Mahdianpari et al. [60]presented a survey of DL tools for classification of wetland classes and checked seven power of deep networks using multispectral remote sensing imagery[49].

4.4 Other Domains

The development of smart agriculture inevitably requires automated machines. To operate it safely without supervision, it should have the function of detecting and avoiding obstacles. The work by Christiansen et al. [61] detected unusual surrounding areas or unknown target types with distant and occlusion targets using Deep Anomaly, which combined DL algorithms. Compared to Faster R-CNN and most CNN models, Deep Anomaly had better performance and accuracy and requires less computation and fewer parameters for image processing, which was suitable for real-time systems. In contrast to[61],the work by Steen et al. [62] can detect an obstacle with high accuracy in the field of row crops and grass mowing. However, it cannot recognize people and other distant objects. The work by Khan et al. [63]used popular DL networks to estimate vegetation index from RGB images. They used a modified AlexNet deep CNN and Caffe as the base framework for implementation. The work by Kaneda et al. [64] presented a novel prediction system for plant water stress to reproduce tomato cultivation. The work by Song et al.[65] combined DBN and MCA to predict soil moisture in the Zhangye oasis, Northwest China. The workby Wang et al. [66] presented used CNN, ResNet, and modified architecture ResNeXt to examine lousy blueberries. The work by Mandeep et al. [67] employed H2O model to estimate evapotranspiration in Northern India and got a better performance than four learning methods, including DL, generalized linear model (GLM), random forest (RF),and gradient boosting machine (GBM) [49].A research on Deep Learning For Remote Sensing Image Classification For Agriculture Applications is proposed [15].

In another study in 2020, Shiva et al.[12] proposed an automatic image-based plant pheno typing approach for stress classification in plant shoot images. They examined the impact of stress, here, nitrogen deficiency for three weeks. They classified the samples into three classes, healthy, semi-stressed and severely stressed. For healthy plants,100% nitrogen was available, for semi-stressed they provided only 50% of the nitrogen requirement and for severely stressed, only 10% of the nitrogen requirement was given. Results have shown that the performance of CNN with background was 75%and without background was 83% [1].

Another problem addressed in some of the research works that have been reviewed was smart farming. Aiming to achieve this objective, Horng et al. in their work [8] trained neural network models to determine the maturity of tomato plant through object detection and then harvest the mature crops using robotic arm. They have used a combination of MobileNet and SSD model. MobileNet was used for feature extraction from the input image and SSD was used for categorizing the image features. In another work of 2020, Sudiantoet al. [17] achieved the objective of sorting and grading of chilly after harvesting whether its quality is good or not. They used You Look Only Once (YOLOv3) which is a deep learning algorithm based on CNN. The main advantage of YOLOv3 is that it has multi-scale prediction and better backbone classifier which helped it to achieve an accuracy of 99.4%. In the detection of good quality chilies. In their work of 2018[18], Jaromir et al. worked on recognizing the quality of seeds in respect to their viability of sowing. They employed CNN-F architecture with transfer learning. Their experiment showed that the accuracy with data augmentation was 87.1% and without augmentation was 84.4% . In [19], Ignacio et al. achieved the objective of recognition of blueberries images in the rooting stage in smart farms in Chile. They designed a CNN with 8 layers using TensorFlow. The system was able to detect presence of living plants in tray, absence of living plants in tray and no tray at all. A robot was used at the Adventist University of Chile which contains a carriage that runs along a hot bed with container trays of blueberry plants. It achieved an accuracy of 86% in its task[1]. A framework for Internet of Things-enabled smart farming applications. In 3rd World Forum on Internet of Things (WF-IoT) is developed [15].

V. CONCLUSION

In this paper, the author has surveyed the development of deep neural-based work efforts in the agriculture domain. Analysed the works on the applications of deep learning and the technical details of their implementation. Each work was compared with existing techniques for performance. It has been found that deep learning has much better results than other image processing techniques. Moreover, with the advances in computer hardware, deep learning will receive more attention and broader applications in future research. Neural networks are in a real sense one of the best solutions to a few agriculture problems. Undeniably, the implementation of ANN to precision agriculture plays a crucial role in potential assessment of the idea of precision farming as a viable way of fulfilling the food demands of the planet. Nonetheless, in order to ensure viability of future food demands, armers welfare and economic growth, more work on the impacts of ANN on agricultural problems has to be carried out. This paper aims to encourage more researchers to study dee plearning to settle agricultural issues such as recognition, classification or prediction, relevant image analysis, and data analysis, or more general computer vision tasks. This survey would create interest in other researchers to experiment deep learning in various agricultural issues which involve image classification or prediction related to computer vision and image analysis or more generally to data analysis and identification. The overall benefits of deep learning are encouraging for its further use towards smarter, more sustainable farming and more secure food production.

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