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Data Collection of Groundnut Farmers through Deep Learning Techniques; A Review

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ABSTRACT

Deep learning methods have also gained popularity for crop classification. Studies have used 1D CNN and 2D CNN architectures, RNNs, convolutional RNNs and 3D CNNs.Among the limited works that study crop type classification in Africa, we note that incorporating both radar and optical information often improves performance, but the often small size of the dataset makes generalization question-able.

Basically, the most popular annual productivity seed or grain is groundnut (*Arachis hypogaea* L). The groundnut is a well-known source of nutritious food that contain healthy ingredients such as fat, vitamins, dietary fibers, minerals and protein. The main seed oil crop in India is groundnut, which has taken the productivity area of 208,149 ha and it yields 0.45 million tons of groundnut. Hence, the controlling procedure of pests and diseases can enhance the productivity of groundnut. The report of India has shown; there may 40–60% of losses yield in groundnut production.Sometimes the ranges may increase to 93% based on the different diseases in groundnuts like collar rot, stem rot, leaf spot, etc.. In south India, when compared to the overall performance of other pests, the leaf miner (*Aproaeremamodicella* Dev.) is the most popular and well-known pests that mainly affect the leaf of the groundnut. These pests are mostly chemical, so many more pesticides are suggested to control the pathogen and insects. Therefore, the early stage of infestation in fungal disease symptoms identification and correction is a challenging task. In every part of the groundnut, the plant is affected by various diseases.In Pakistan, the enlarger number of diseases can affect the groundnut. Moreover, the oil obtained from the groundnut is used for cooking and soap production. After the oil extraction, the remaining products are used in poultry feed. However, the raw, boiled and roasted groundnut seeds are used for eating. Mostly, the groundnut plants are caused by fungal, viral, rust and leaf spot diseases. These made the losses in economic and productivity. The fungal disease, such as leaf blight, leaf scorch, pepper spot, Alternaria, Phomopsis, Phoma, Phyllosticta, Drech-slera leaf blight, anthracnose and Cylindrocladium leaf spot, affects the groundnut plant. Nowadays, the process of identifying groundnut disease is a major challenging problem. The various image processing, artificial intelligence and graphical processing units are widely used to detect the plant diseases.

Particularly, many of the researchers suggested various research techniques and pesticides to

control and manage groundnut diseases. Few of the existing research mechanisms are formulated as follows. Agriculturists proposed a method of plant growth-promoting rhizobacteria (PGPR) for controlling pests. It is a latent defense method and set in motion systematically based on the pathogen's infection exposure of plants. Scientists introduced the K-nearest neighbor (K-NN) method for the detection of plant diseases. The method is used to extract the features, and it classifies the data based on their measures. But it does not predict the diseases correctly. They also proposed a powerful and flexible method of machine learning mechanism to make the amalgamation of well suitable system knowledge. The main advantage is few of the learning algorithms are used in agricultural fields. The process of classification models with high spectral agricultural image decisions making is used in the regression of logistic and decision trees. Therefore, a rural area in America initiates the application-oriented smart-phone to analyze the groundnut and plant diseases. The well popular mobile application of Plantix provides many useful ideas and tips for the farmers in the field of agricultural. The leaf diseases of groundnut were mainly focused on using Plantix application.Furthermore, the convolution neural network is the major part to detect and treat the plant diseases. So, many of the researchers suggested various artificial intelligence-based neural network techniques and introduced a deep neural network method for the groundnut leaf disease classification. Different kinds of training set are used to evaluate the performance of deep neural net-work. The groundnut leaf disease symptoms are detected at the initial stage. They also presented a convolutional neural network (CNN) architecture for the detection of plant diseases. The hierarchical evocative feature extractor and classifier is a flexible framework of CNN, and it permits the meaning of the model. There is the extension of CNN topology by the stacking of additional convolutional layers. Based on million plant dataset images, various classes with 1000 dataset images are trained and classified using CNN. It introduced the combination of back-propagation with a neural network (NN)-based concept for the identification of cotton diseases. In the initial stage, the visible area of the plant like leaves and stem diseases is identified by using phone window application with images. And proposed convolutional neural network (CNN) method for the plant disease image classification and recognition. It is manually to extract the features, and it is highly robust against feature learning. Further research recommended the popular approach of convolutional neural network (CNN); it detects the plant diseases very accurately and effectively. The CNN is converted into the space of low dimensional, and the network structural information is protected. The CNN network is well suitable for recognizing the leaf Diseases.

In the general computer vision community, we relate our task with semantic segmentation for video, as well as action recognition in which several temporal observations are used to make predictions. Some of the first work in exploring CNNs for video classification began with in which video frames were concatenated and input into a single stream model. This work was extended to use two data streams to model temporal features by pre-computing optical flow vectors, further extended for longer time-range modeling and with learnable flow vectors. Recently it suggestedto build upon work from RNNs and use a CNN + LSTM network for incorporation spatial and temporal information. A similar work uses a CNN and convolutional RNN to predict pixel level labels of objects vs background for semantic segmentation in video. 3D convolutions are applied to video volumes in, and attention was incorporated with a 3D CNN network in Carreira and also incorporate 3D models into two stream networks.

Key Words;RNNs; CNN; LSTM network. Alternaria, Phomopsis, Phoma, Phyllosticta, Drech-slera leaf blight, anthracnose and Cylindrocladium leaf spot

INTRODUCTION AND REVIEW

Fundamentally, the most popular factor in human survival is agriculture. In the United Nations, based on the organization of food and agricultural products (Dankelman and Davidson, 2013), India is one of the best countries in the field of the agricultural sector. Peoples required better\ productivity and healthy foods. Moreover, agricultural plants and products are affected by various diseases. Many of the diseases can entirely affect the productivity of crop\ fields, and it made a big economic loss to the farmers (Singh. 2018). Generally, the plant diseases are visible with different learning and skills to monitor the symptoms of plant diseases. Mainly, the vegetables, nuts, fruits, grains and legumes qualities and productivities are affected by various kinds of plant diseases. Naturally, the equipment of photosynthesis was damaged in the presence of various diseases in the plants and it may cause plant growth. While 85% of plant diseases are affected by the organism of fungal or fungus. The remaining 20% are affected by viruses, bacteria, nematodes and viroids.

Basically, the most popular annual productivity seed or grain is groundnut (*Arachis hypogaea*L). The groundnut is a well-known source of nutritious food that containhealthy ingredients such as fat, vitamins, dietary fibers, minerals and protein (Kylberg, 2011). The main seed oil crop in India is groundnut, which has taken the productivity area of 208,149 ha and it yields 0.45 million tons of groundnut. Hence, the controlling procedure of pests and diseases can enhance the productivity of groundnut (Pi-mentel and Burgess, 2014). The report of India has shown; there may 40–60% of losses yield in groundnut production.

Sometimes the ranges may increase to 93% based on the different diseases in groundnuts like collar rot, stem rot, leaf spot, etc. (Bharate and Shirdhonkar, 2017. In south India, when compared to the overall performance of other pests, the leaf miner (*Aproaeremamodicella* Dev.) is the most popular and well-known pests that mainly affect the leaf of the groundnut. These pests are mostly chemical, so many more pesticides are suggested to control the pathogen and insects. Therefore, the early stage of infestation in fungal disease symptoms identification and correction is a challenging task. In every part of the groundnut, the plant is affected by various diseases.

In Pakistan, the enlarger number of diseases can affect the groundnut. Moreover, the oil obtained from the groundnut is used for cooking and soap production (Tuzun, 2001). After the oil extraction, the remaining products are used in poultry feed. However, the raw, boiled and roasted groundnut seeds are used for eating. Mostly, the groundnut plants are caused by fungal, viral, rust and leaf spot diseases (Woodward et al., 2006). These made the losses in economic and productivity. The fungal disease, such as leaf blight, leaf scorch, pepper spot, Alternaria, Phomopsis, Phoma, Phyllosticta, Drech-slera leaf blight, anthracnose and Cylindrocladium leaf spot, affects the groundnut plant. Nowadays, the process of identifying groundnut disease is a major challenging problem (Ojala*et al*., 2002). The various image processing, artificial intelligence (Sundararaj*et al*., 2018; Sundararaj, 2016, 2019a,b; Traore*et al*.,2018; Rejeesh, 2019) and graphical processing units are widely used to detect the plant diseases (Traore*et al*.,2018)).

Particularly, many of the researchers suggested various research techniques and pesticides to control and managegroundnut diseases. Few of the existing research mechanisms are formulated as follows. Bakker et al. (2001) proposed a method of plant growth-promoting rhizobacteria (PGPR) for controlling pests. It is a latent defense method and set in motion systematically based on the pathogen’s infection exposure of plants. El Houby (2018) introduced the K-nearest neighbor (K-NN) method for the detection of plant diseases. The method is used to extract the features, and it classifies the data based on their measures. But it does not predict the diseases correctly.Yang et al. (2003) proposed a powerful and flexible method of machine learning mechanism to make the amalgamation of well suitable system knowledge. The main advantage is few of the learning algorithms are used in agricultural fields. The process of classification models with high spectral agricultural image decisions making is used in the regression of logistic and decision trees. Therefore, a rural area in America initiates the application-oriented smart-phone to analyze the groundnut and plant diseases (Toseefand Khan. 2018). The well popular mobile application of Plantix provides many useful ideas and tips for the farmers in the field of agricultural. The leaf diseases of groundnut were mainly focused on using Plantix application.

Furthermore, the convolution neural network is the major part to detect and treat the plant diseases. So, many of the researchers suggested various artificial intelligence-based neural network techniques. Mohanty et al. (2016) introduced a deep neural network method for the groundnut leaf disease classification. Different kinds of training set are used to evaluate the performance of deep neural net-work. The groundnut leaf disease symptoms are detected at the initial stage. Russakovsky et al. (2015) presented a convolutional neural network (CNN) architecture for the detection of plant diseases. The hierarchical evocativefeature extractor and classifier is a flexible framework of CNN, and it permits the meaning of the model. There is the extension of CNN topology by the stacking of additional convolutional layers. Based on million plant dataset images, various classes with 1000 dataset images are trained and classified using CNN. Li et al. (2010) introduced the combination of back-propagation with a neural network (NN)-based concept for the identification of cotton diseases. In the initial stage, the visible area of the plant like leaves and stem diseases is identified by using phone window application with images. Kamilaris and Prenafeta-Boldu´ (2018)proposed convolutional neural network (CNN) method for the plant disease image classification and recognition. It is manually to extract the features, and it is highly robust against feature learning. Wan et al. (2019) were recommended the popular approach of convolutional neural network (CNN); it detects the plant diseases very accurately and effectively. The CNN is converted into the space of low dimensional, and the network structural information is protected. The CNN network is well suitable for recognizing the leafDiseases.

The process of automatic feature extraction is a key point of deep learning. The required problem features are selected automatically, and there is no need for any fixed or handcrafted features. The explicit features are selected, and it reduces the specialist works (i.e. traditional pattern recognition). Therefore, the different kinds of supervised, semi-supervised and unsupervised problems were recovered. The hidden layers consist of many layers, but a minimum amount of three hidden layers are applicable.

The nonlinear feature transformation of one phase is presented in deep learning (Lecun*et al*.,2015). Significantly, the single sets of features are trained by using the group of neurons in every hidden layer and it depends upon the previous layer output. The amount of hidden layer is raised as well as the data generalization and complexity also get increased. The trainable classifier with a hidden layer carried out low-level, mid-level and high levels of the feature extraction process (Lecun*et al*.,2015).Mostly, the researchers have classified the deep learning concept into four types: they are Boltzmann Machines, Auto Sparse, Convolutional Neural Network and Autoen-coders (Guo*et al*.,2016).Shapes and objects with mid-and high-level features are found by using the remaining layers (Lecun*et al*.,2015).Mathematically, the term convolution is the numerical ideas and ethics based on the process of feature transformation. Based on mathematics, the algebraic topology of convolution is denoted employing transformation functions such as ‘a’and ‘’b,respectively, where abare the two real complex number convolutions (Lin *et al*., 2013).

Precision agriculture (PA) can be utilized for a variety of purposes, such as identification of plant pest, identification of weed, production of crop yield, and detection of diseases in plants. Roofing out the scope of bringing in the groundnut cultivation under precision farming, will surely lead to increased productivity by thus ensuring farmers economical sustainability. As groundnut stays to be the major oil seed crop in India, controlling its diseases and identifying it at the earlier stage may enhance the productivity of

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groundnut (Pimentel and Burgess, 2014). According to an Indian assessment, groundnut cultivation may experience 40–60 percent output reductions. Because of varying diseases in groundnuts based on leaf, root and stem, the ranges can sometimes reach 93 percent too. To improve the acknowledgement rate and precision of the findings, smart precision technologies like as ML and DL, as well as IoT, have been deployed. We conducted a complete analysis of Deep Learning Techniques (DL) Techniques in leaf disease diagnosis in this research, and based on the review, we intend to investigate a deep learning model based on the state of art of VGG16 Deep learning model with two types of optimizers (RMSprop and ADAM) for recognizing and classifying groundnut crop leaf diseases.

Deep learning would soon become the standard approach for identifying images, according to AnnalBarbedo(2019). On average, our method's accuracy was 12% higher than that of experts who used the actual image. Despite this, even when more than ten diseases had been considered, each plant had a precision of less than 75%. Although the study does not cover all possible circumstances, the results confirms that deep learning approaches can be used to detect and identify plant diseases provided there is enough data.

Data mining is the process of extracting useful knowledge or information from large amount of data. In digital generation, data mining is becoming an increasingly important tool to transform data into information. When the Data mining techniques are used with agriculture data, the term is known as precision agriculture. The main aim of the work is to improve and substantiate the validity of yield prediction, which is useful for the farmers. Agricultural crop production depends on various factors such as biology, climate, economy and geography. Several factors have different impacts on agriculture. So previous year's researchers used appropriate statistical methodologies. A large number of variables can affect agronomic traits such as yield.

Yield prediction is a very important agricultural problem. Any farmer is interested in knowing how much yield he is about to expect. In the past, yield prediction was performed by considering farmer's experience on particular field and crop. Consider that data are available for some time back to the past, where the corresponding yield predictions have been recorded. In any of Data Mining procedures, the training data is to be collected from some time back to the past and the gathered data is used in terms of training which has to be exploited to learn how to classify future yield predictions. Crop yield prediction is an important area of research, which helps in ensuring food security all around the world.In this work, we apply deep-learning based semantic segmentation models to remotely sensed data in order to map crop type from space. Specifically, given a temporal sequence of satellite imagery over an agricultural area, we classify each pixel as one of several different crop types.

As described above, we explore crop type classification in Ghana and South Sudan, where this problem is particularly relevant (World Food Programme, 2018;UN Economic

Commission for Africa, 2014 and The sustainable development goals report, 2018).

Cropland classification studies often use many temporal observations as input, since the spectral properties of crops change throughout a growing season (Schultz*et al*., 2015; Ndikumana*et al*., 2018 andFoerster*et al*., 2012). In addition, a combination of both optical and radar data has oftenlead to improved results for land cover and crop type classification (Inglada*et al*., 2016; Kristof*et al*., 2018 and Joshi*et al*., 2016).

In the general computer vision community, we relate our task with semantic segmentation for video, as well as action recognition in which several temporal observations are used to make predictions. Some of the first work in exploring CNNs for video classification began with (Gomez*et al*., 2016), in which video frames were concatenated and input into a single stream model. This work was extended to use two data streams to model temporal features by pre-computing optical flow vectors, further extended for longer time-range modeling (Feichtenhofer*et al*., 2016 andWang*et al*., 2015) and with learnable flow vectors (Zhu*et al*., 2018). Ngand Donahueet al. (2015) instead build upon work from RNNs and use a CNN + LSTM network to incorporate spatial and temporal information. A similar work (Valipour*et al*., 2016) uses a CNN and convolutional RNN to predict pixel level labels of objects vs background for semantic segmentation in video. 3D convolutions are applied to video volumes in, and attention was incorporated with a 3D CNN network in (Yao*et al*., 2015). Carreiraand Fisherman(2017) also incorporate 3D models into two stream networks, further extended in (Diba *et al*., 2017).

In recent years, deep learning methods have also gained popularity for crop classification (Kamilaris and Prenafeta-Boldu, 2018). Studies have used 1D CNN (Yaping*et al*., 2018;Pelletier*et al*., 2019 and Zhong*et al*., 2018) and 2D CNN architectures (Kussul*et al*., 2018 and Karakizi*et al*., 2018), RNNs (Marc and Marco, 2017 and Hao*et al*., 2015), convolutional RNNs (Marc and Marco, 2018), and 3D CNNs (Shunping*et al*., 2018).Among the limited works that study crop type classification in Africa, we note that incorporating both radar and optical information often improves performance, but the of-ten small size of the dataset makes generalization question-able (Gerald*et al*., 2014).

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