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Analysis of Crop Detection and Monitoring Methods

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Abstract

In this paper, a survey has been performed on deep learning techniques for supporting farmers in monitoring the crops and their yields. The study has been done on the specific models and frameworks employed for agriculture issues. Also, a study has been done on the data set used, and the overall performance achieved according to the metrics. The comparison listed on basis of few parameters and the findings indicate that deep learning provides high accuracy and is commonly used for image processing techniques. This survey will surely be beneficial for farmers and researchers to find out the results about trends and statistical information of crops, updating facilities and land availability which can in turn help in improving production.

Keywords: Convolutional Neural Networks technique (CNN), Decision tree (DT), Deep learning technique, Object-based Crop Identification and Mapping (OCIM), Support Vector Machine (SVM)

Introduction

Now a days many researchers are focusing on agricultural research for helping the farmers to improve their crop yield. For providing a complete monitoring a deep learning-based system for efficient crop detection is important which will also be helpful to them in notifying earlier for further control [4]. It will help them to increase the productivity and earn maximum profit.

Crop identification at the earlier will help in scalability, that means it will allow to automatically analyze large amounts of data in detail, which saves money, time and teams can focus on more important tasks. It will also be helpful in real-time analysis that means it can help to immediately identify details of a crop which helps the farmer to get knowledge of which crop to sow that will give them a better profit.

Today the farmer is not having proper knowledge about which crops to grow in his vicinity that can give him better profits. Due to which they face problems regarding demand of their crops in the market and it becomes difficult to bear the expenses of the crop yield. Thus, for this data of the crop can be taken from farmers and then analysis can be done and after those results of the crop can be shown in form of graphsto farmer about the crop yield.

The most popular technique which is gaining popularity today is Deep learning because of its large potential and this is the reason of motivation for doing this survey. The other techniques used for analyzing images include machine learning, artificial neural networks, linear polarizations, vegetation indices (NDVI) and regression analysis. Deep learning belongs to the machine learning computational field and is like ANN and it provides a hierarchical representation of the data by means of various convolutions. This allows higher precision and performance by larger learning capabilities.

Objectives

The objectives of this research paper is to help the researchers in following ways:

- To provide the statistics of crops in the farmer's area
- To provide the data of crops in demand in that area with the help of experts
- Can be over multiple mandis to communicate and deal with each other
- To ensure maximum profitability for farmers

Benefits

- Helpful for local Agriculture market growth
- Helpful in production Analysis
- It can be extended for disease detection and prevention [14]
- Users will get information about statistics of crops in its area which will help them in selection of crops to be grown in their field.

Preliminaries

Agriculture is the largest source of livelihoods in India. Around 82% of farmers are small and marginal and 70% of its rural households still depend on agriculture for their livelihood. Farmers quite often face difficulties regarding the farming structure, and they are unable to choose the right crop based on the market scenario. The most promising solution for this is the automatic plant image detection for which the sophisticated models have been proposed. [9] It is time consuming to determine the name of the plant species even for the experts. Plant identification aims at determining the name of species based on observations [10].

If we can provide a proper statistic of the crops which are in demand in any area, then it will help farmers to decide which crop they should choose and will be able to make more profit.

Methodology

In the domain under investigation, the bibliographic analysis consisted of two steps:

(a) Collection and compilation of related work.

(b) Few papers are selected from the previous step and few more are added, and a systematic examination and analysis is done in the form of table considering essential parameters and performance.

In the first phase, the scientific databases are used to search for research papers with sufficient implementation of the DL technique and findings. The papers chosen in the previous step were analyzed one by one in the second step, with the following research parameters:

1. Methodology: What was the method/ technology and form of DL-based models used in general?

2. Dataset: What were the data sources and data sets that were used?

3. Review: What were the methods used for feature extraction

4. Future Aspects: What were the gaps or output difference while equating the specified method to other methods and so what can be done in future.

5. Accuracy: What was the overall performance based on the chosen metric?

Deep learning and Different Techniques

The strongest benefit of Deep Learning is extraction of features from raw data (LeCun et al., 2015) [11]. DL because of its massive parallelization, can solve more complex problems quickly. DL method can improve classification accuracy or error can be minimized in regression problems if there are sufficiently large datasets. It consists of different components like, Convolutional Neural Networks, Unsupervised Pre-trained Networks, Recursive Neural Networks, Recurrent Neural Networks,). Classical ML can be extended by adding more "depth" to the model through multiple levels of abstraction (Schmidhuber, 2015; LeCun and Bengio, 1995) [12]. If there are large datasets available, then classification accuracy can be increased, or error can be reduced in regression problems using complex models of DL.

To evaluate performance, various metrics have been employed by the authors, specific to the model used in each study. As different metrics are employed for different tasks it is difficult to compare between papers, considering different models, datasets and parameters. It is an important point here to examine whether the authors had tested their implementations on the same dataset or used different datasets to test their solution.

Comparison of performance

For efficient crop detection many articles, papers and books on deep learning have been written from the past set of years. So, to examine how DL outperform other approaches implemented for comparison purposes a critical survey has to be done.

“Deep neural networks with transfer learning in millet crop images” [5]In this paperthe proposed approach identifies a mildew disease in crop millet. An approach based on feature extraction of a pre trained based on ImageNet.

Methodology

The proposed methodology based on the CNN model VGG16 that is pre trained on ImageNet uses the feature extraction that is an approach of transfer learning.

- *VGG16 overview*

For ImageNet the commonly used architecture is VGG16. It takes a 224 224px image as input and returns a 1 000px vector with the probabilities of belonging to each class. 13 convolution layers, 3 completely linked layers, and 5 pooling layers make up VGG16 (as shown in Fig. 1). The ImageNet image is used to remove features using the 16 convolutional layers. Each convolution layer has a 3 3 multiple filters with a stride of 1px. Softmax is the final layer, which is used for classification. ReLU is used as an activation feature in each convolution layer. The proposed approach for feature extraction makes it possible to modify the classification of 1000 classes of ImageNet to a classification of two classes consisting in determining as outputs the presence or the absence of mildew. The new network is obtained is shown in Fig 2.

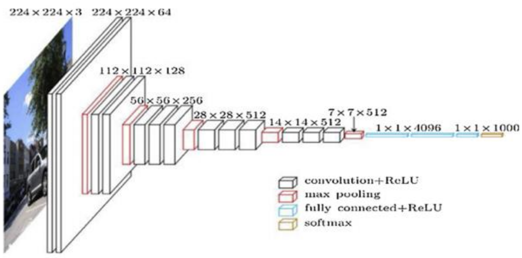

Fig 1. VGG16. Architecture

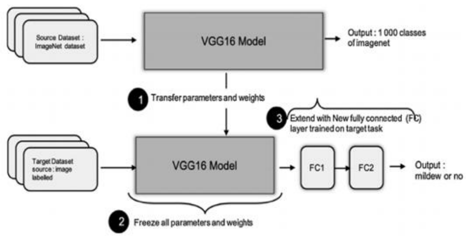

Fig 2. Proposed approach for feature extraction

- *Transfer learning*

Deep learning algorithms necessitate a massive dataset and a long time to train the various weights and millions of parameters of a deep network. This allows for accuracy in information representation. To begin, data augmentation is a technique for the size of datasets. It avoids overfitting by using image transformation. Second, having computational power to train a deep network was made possible by the Graphical Processing Unit (GPU). Also needed is the similarity (same function, same distribution) of the training and testing datasets. In fact, bringing these elements together is difficult and costly. Agricultural regions, on the other hand, have a deficit in public datasets. The scientists create their own scheme. The researchers develop their own system and that requires a long time of work.

Result

The proposed approach identifies a mildew disease in crop millet. An approach based on feature extraction of a pre-trained image based on ImageNet. The performance of transfer learning gives 95.00% accuracy.

An Efficient Crop Identification Using Deep Learning [1]In this paper for detecting the suitable crop the recurrent neural network is utilized for the observed environmental conditions from the field and also the suggestions are provided about the desired crop that can be grown in that field or not.

Methodology

Logistic Regression

Logistic regression is a mathematical model in which the base type of a logistic function is used to model a binary dependent variable. The five types of crops, rice, wheat, barley, tomato, and chile, are the different categories of outputs that are obtained based on the input values obtained from sensors such as moisture sensors temperature sensors, rainfall sensors and humidity sensors

- *Random Forest Classifier*

Random forests are a classification learning method that works by training multiple decision trees and producing production as the classes' mode or individual trees' mean prediction. Decision trees' habit of overfitting to their collection of training data is disrupted by random forests. A decision tree is a well-known classification system that is used in a variety of machine learning tasks. The suitable crop that can be grown in the area can be classified using a random forest classifier based on values such as temperature sensor values, humidity sensor values, rainfall sensor values, and moisture sensor values.

- *Support Vector Machine*

One of the most efficient supervised learning methods for analysing data and performing classification and regression tasks is the support-vector machine. Each sample in the training examples set is assigned to one of the groups, and the SVM training algorithm creates a model that assigns new examples to one of the groups. Similarly, SVM will identify the crop and fine the appropriate crop for the current weather conditions based on the qualified values of temperature sensor, humidity sensor, rainfall sensor, and moisture sensor.

- *Decision Tree Classifier*

In the field of computer science, a decision tree classifier builds a tree from the data given and effectively classifies the data. It converts observations about an object into assumptions about the object's target value. For classification, it is one of the statistics modelling methods, machine learning, and data mining. The regression trees are built for the continuous goal values. In this paper appropriate type of crop to be grown in that area is identified based on the values obtained from the temperature sensor, humidity sensor, rainfall sensor, and moisture sensor.

- *Multilayer Perceptron*

The feed forward class of artificial neural networks includes multilayer perceptron’s. A multilayer perceptron has at least three layers of nodes: an input layer, one or more hidden layers, and an output layer. In this paper the type of crop that can be grown as the output using this technique is classified, using sensor values obtained from temperature sensor, humidity sensor, rainfall sensor, and moisture sensor as input values. Recurrent Neural Network

- Recurrent Neural Network

The most suitable crop that can be grown in the area for the current and future climatic conditions is categorized using values obtained from sensors such as temperature, humidity, rainfall, and moisture sensors. Deeper Recurrent Neural Networks produced outstanding results in a variety of image classification problems. The network's ability to collect features could be enhanced by adding more layers to the node. Fig. 3 depicts the structure of a recurrent neural network.

Table 1. Accuracy of crop prediction

S.No	Algorithm	Predicted crop	Accuracy
1.	Logistic Regression	Wheat	95.5%
2.	Random Forest Classifier	Wheat	96.7%
3.	Support Vector Machine Classifier	Wheat	97.8%
4.	Decision Tree Classifier	Wheat	94.7%
5.	Multilayer Perceptron	Wheat	93.6%
6.	Recurrent Neural Network	Wheat	98.3%

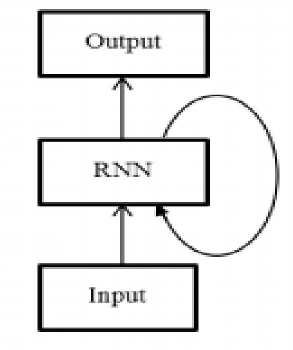

Fig. 3. Structure of Recurrent Neural Network.

Result

Table 1 represents the accuracy of crop prediction. There are 10,000 records in the dataset, which are divided into training and testing files. 67 percent of the records in a database of 10,000 are used as training data, while the remaining 33% are used as research data. The experiment was carried out by feeding current weather conditions into machine learning algorithms such as random forest, decision tree, logistic regression, support vector machine, multilayer perceptron, and RNN, as well as temperature sensor values, humidity sensor values, rain sensor values, and moisture sensor values. Then, using the algorithms described above, a suitable crop is found. If the farmer wishes to grow a different crop, the machine will be able to advise whether the desired crop can be grown. Recurrent Neural Network Algorithm IS USED to boost the accuracy and classify the most suitable crop for the current and future climatic conditions, as machine learning algorithms are less accurate than deep learning algorithms.

Deep-plant: Plant Identification with convolutional Neural networks [9] In this paper to gain intuition on the chosen features from the CNN model a visualisation technique based on the deconvolutional networks (DN) is utilized. Using these CNN features superiority and consistency was shown with different classifiers in experimental results compared to the state-of-the art solutions.

Methodology

In this paper, deep learning is used in a bottom-up and top-down manner for plant identification. In the former, a convolutional neural networks (CNN) model is used to learn the leaf features to perform plant classification. In the latter, deconvolutional net- works (DN) is employed to visualize the learned features. rather than using the CNN as a black box mechanism. This is done in order to gain visual understanding on which features are important to identify a leaf from different classes.

Empirically, the method mentioned in this paper outperforms state-of-the-art approaches [6,7] using the features learned from CNN model in classifying 44 different plant species. Fig. 4 depicts the overall framework of the approach used in this paper.

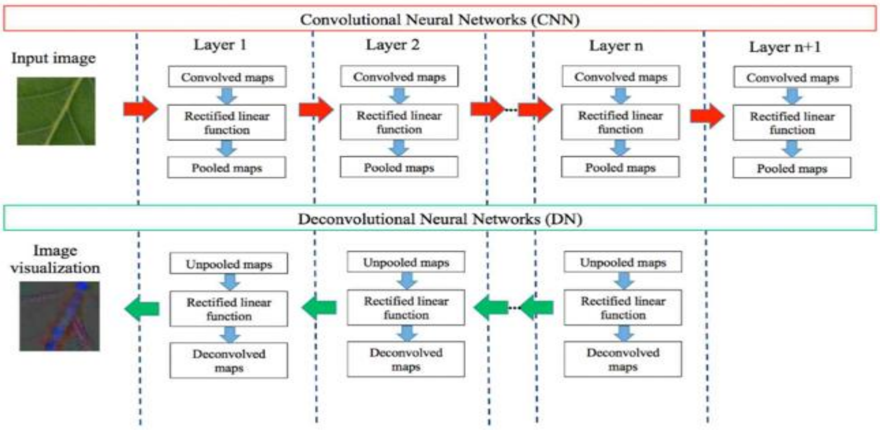

Fig 4. Deep learning framework in a bottom-up and top-down manner to study and understand plant identification.

Techniques

Initially, a CNN model is proposed replacing the need of designing hand-crafted features as to previous approaches [5, 13, 6, 7] to automatically learn the features representation for plant categories. Then the feature representation learnt by the CNN model through a visualisation strategy based on the DN are identified and diagnosed. This is to provide an insight to re- searchers on how the algorithm "see" or "perceives" a leaf and also to avoid the use of the CNN model as a black box solution. Finally dataset named as MalayaKew (MK) is also collected with full annotation.

Result

A new leaf dataset, collected at the Royal Botanic Gardens, Kew, England named as MalayaKew (MK) Leaf Dataset which consists of 44 classes is employed in the experiment. Fig. 5 illustrates the samples of the leaf dataset which is very challenging as leaves from different classes have very similar appearance. A data (D1) is prepared to compare the performance of the trained CNN.

Table 2: Performance Comparison

Feature	Classifier	Accuracy (%)
From Deep CNN (D1)	MLP	0.977
From Deep CNN (D1)	SVM (linear)	0.981
From Deep CNN (D2)	MLP	0.995
From Deep CNN (D2)	SVM (linear)	0.993
LeafSnap [3]	SVM (RBF)	0.420
LeafSnap [3]	NN	0.589
HCF [9]	SVM (RBF)	0.716
HCF-ScaleRobust [9]	SVM (RBF)	0.665
Combine [9]	Sum rule (SVM (linear))	0.951
SIFT [11]	SVM (linear)	0.588

Fig 5: Sample of the 44 plant species

A comparative performance evaluation of the CNN model on plant identification(MK leaf dataset) on the basis of different classifiers, MLP = Multilayer Perceptron, SVM = Support Vector Machine, and RBF = Radial Basis Function is shown in Table 2. It is noticed that using the features learnt from the CNN model (98.1%) outperforms state-of-the-art solutions [4, 3, 5] that employed carefully chosen hand-crafted features even when different classifiers are used.

From the experimental results, it has been found that learning the features through CNN can provide better feature representation for leaf images compared to hand-crafted features.

Object-based crop identification using multiple vegetation indices, textural featuresand crop phenology[1]In this paper decision tree (DT) and OBIA algorithms are combined to develop a methodology, named Object-based Crop Identification and Mapping (OCIM), for a multi-seasonal assessment of a large number of crop types and field status. The objectives were to: 1) explore the relationship of textural features and multiple vegetation indices with the studied crops at parcel scale; 2) evaluate the contribution of the short-wave- infrared, near-infrared, visible, and spectral regions in the identification of crop types and crop management techniques; and 3) determine the influence of crop discrimination in different growing-season periods.

Methodology

In this paper a methodology named Object-based Crop Identification and Mapping (OCIM) is proposed, which combines DTs and OBIA for the assessment of a field status in the agricultural region and large number of major crop types of Yolo County, California as this county has diversity of cropping systems. The OCIM methodology consists of mainly two consecutive phases: 1) delimitation of crop-fields by image segmentation and, 2) Based on physically interpretable thresholds, application of decision rules of selected texture and spectral features which characterize every studied crop as affected by crop calendars, growing-season period, and soil management techniques.

The crop calendars through regular field trials of each studied crop conducted in Yolo County, consultation with experts and literature research as shown in Fig. 6.

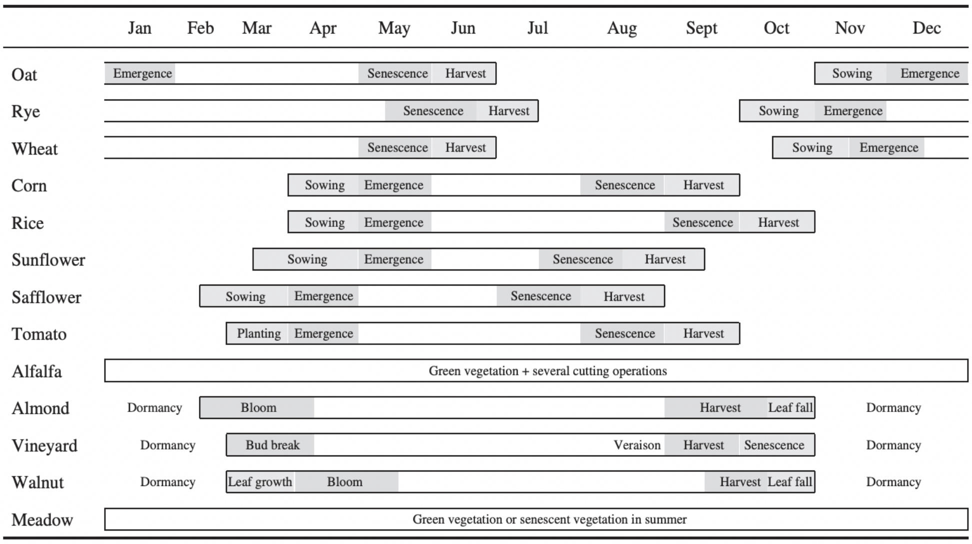

Fig. 6. Crop calendar for major crops growing in Yolo County (CA).

Result

The OCIM methodology developed in this paper was suitable for crop identification at different phenological stages, object-based feature selection and field conditions in Yolo County agroecosystem. This methodology was developed in four different scenarios (combinations of three or two periods) and evaluated by using three independent ground-truth dataset and two consecutive validation methods (Table 3)

Table 3. Evaluation of OCIM methodology as affected by growing-season period.

Period	DT validation			Imagery classification assessment (overall accuracy)[a]			
	N[b]	χ^{2c}	Error rate (%)	Permanent crops[d] (%)	Summer crops[d] (%)	Winter cereals and meadows[d] (%)	All crops (%)
Mid-spring, early-summer, late-summer	36	1283.60	9	76	84	75	79
Mid-spring, early-summer	35	1097.93	16	67	79	72	64
Mid-spring, late-summer	32	1155.72	13	74	66	68	67
Early-summer, late-summer	31	1230.94	12	68	82	67	73

[a] Based on the confusion matrix method calculated from 650 independent test fields (Table 6). The overall accuracy of permanent crops, summer crops and winter cereals and meadows shows the accuracy among the specific fields of each group of crops.
[b] Number of splits used in the DT model.
[c] Likelihood-ratio chi-square statistic.
[d] Permanent crops: alfalfa, vineyard, almond and walnut; summer crops: corn, rice, safflower, sunflower and tomato; winter cereals: oat, rye and wheat.

The OCIM methodology involves several consecutive steps and provides three levels of crop identification. After segmentation of remote images into realistic and homogeneous areas, cropland was firstly discriminated between permanent crops, summer crops, winter cereals and meadows. Afterwards, the model defines which crop is growing in every parcel and, simultaneously, the intra-class variations attributed to specific crop management operations. This technique helped to optimize the feature selection for crop classification and, consequently, reducing the computational time of image analysis procedure.

Findings

This section gives a detail on the comprehensive review of eight crop identification research papers. The exposition of various articles/papers have been outlined in Table 4.

Table 4: Comparative study of crop detection research work

S. No.	Paper Topic	Year of Publication	Methodology	Dataset	Review	Future aspects	Performance
1.	Deep neural networks with transfer learning in millet crop images. [5]	Coulibaly et. Al. (2018)	An approach using transfer learning with feature extraction to build an identification system of mildew disease in pearl millet is proposed	A small dataset of 124 images of diseased and healthy millet to identify mildew is used.	The proposed method is used for feature extraction to identify disease	One other goal is the selected disease area of crops using the segmentation case in deep learning.	95% Accuracy
2.	An Efficient Crop Identification Using Deep Learning[1]	Agila N, Senthil Kumar P. (2020)	Deep Learning	The dataset consists of 10000 records that are partitioned into training and testing data. Among 10000 records, 67% of records are utilized as training data and the remaining 33% of records are utilized as testing data.	The deep learning concepts was utilized in most of the agricultural research for providing solutions for improving the crop yield estimation, plant disease diagnosis.	The model also suggests that which crop can be grown in that field. Thus, the recurrent neural network model provides high accuracy in detecting the suitable crop identification compared to other methodologies.	95.7% Accuracy
3.	Deep-plant: Plant Identification with convolutional Neural networks[13]	Lee et al (2015)	Convolutional neural networks (CNN) and deconvolution al networks (DN)	44 different plant species, collected at the Royal Botanic Gardens, Kew, England	Learning the features through CNN can provide better feature representation for leaf images compared to hand-crafted features	In future the work can be extended to recognize in the wild.	98.1% Accuracy
4.	Object-based crop identification using multiple vegetation	sé M Peña-Barragán et al. June 2011	Deep learning	The dataset contained 54.309 labelled images for 14 different		Developing an extended rule-set version of OCIM methodology for cropland	95.7% Accuracy

	indices, textural features and crop phenology[7]			crops. SqueezeNet was a good take for the deep learning classification due to its lightweight and low computational need		classification of multi-year satellite imagery	
5.	Classification of Plant Seedling Images Using Deep Learning[2]	Alimboyong Catherine 2018	CNN technologies	A public dataset of 4, 234 plant images is used.	This paper uses a convolutional neural network for training and does data augmentation to identify 12 plant species using a variety of image transforms: resize, rotate, flip, scaling and histogram equalization	The model will be utilized by training it to other types of plants like herbal medicinal plants and other crops in other countries	99% Accuracy
6.	Monitoring and Controlling Rice Diseases Using Image Processing Techniques [8]	Joshi Amrita A. and Jadhav B D (2016)	Minimum Distance Classifier (MDC) and k-Nearest Neighbor classifier (kNN)	15 rice leaf images of four diseases and 70 percent image data has been used for training the classifier and 30 percent has a been used for testing	Image processing techniques like segmentation, feature extraction, and two classifiers were used to establish the classification algorithm	Future work can be to cover other rice diseases. The same techniques can be applied to other crops with little modifications	89.23% Accuracy
7.	Agricultural Crop Identification Using Spot and Landsat Images In Tasmania [3]	BARRETT Rachel. 2000	SPOT AND LANDSAT IMAGES IN TASMANIA	Digital data from SPOT-XS, SPOT-XI and Landsat TM were acquired over the study area during the spring/summer	Digital data from SPOT-XS, SPOT-XI and Landsat TM systems were acquired, for several reasons. As	Digital data from SPOT-XS, SPOT-XI and Landsat TM systems were acquired, for several reasons. As stated by Reid	70.2% Accuracy

				growing seasons of 1997/98 and 1998/99	stated by Reid et al (1993), the high incidence of cloud over Tasmania makes the acquisition of cloud-free images via the Landsat TM system	et al (1993), the high incidence of cloud over Tasmania makes the acquisition of cloud-free images via the Landsat TM system	
8.	Deep Learning for Plant Identification in Natural Environment [14]	Sun, Liu, Wang, and Zhang (2017)	Deep Learning	BJFU100 dataset which contains 10,000 images of 100 ornamental plant species	The ResNet18, ResNet34, and ResNet50 yield a test accuracy of 89.27%, 88.28%, and 86.15%, respectively. The proposed ResNet26 results in 91.78% accuracy on BJFU100 dataset.	The BJFU100 database will be expanded by more plant species at different phases of life cycle and more detailed annotations.	91.78% accuracy

A conclusion section must be included and should indicate clearly the advantages, limitations, and possible applications of the paper. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

Discussion,Conclusion and Suggestions

In this paper, a survey in the agricultural domain with application of deep learning-based research efforts is performed This paper includes outline of current works that done on crop detection and different learning techniques and analysis. We eight main relevant papers have been identified and are examined based on technology used, Domain, Input Output, methodology, future aspects and overall performance according to the performance metrics employed by each paper. Then deep learning technique is compared with other existing techniques, in terms of performance. Observations and findings show that deep learning technique offers better performance in comparison to other popular image processing techniques. It’s also been analyzed that deep learning has been widely used in different areas of agriculture, such as plant classification, plant disease detection, and image translation, yield prediction, weather forecasting. With this survey we have found that deep learning technique can also be helpful and can be applied to other areas of agriculture also.

Our objective of performing this survey is to motivate and help researchers to experiment more with deep learning, applying it for solving various agricultural problems involving statistics of crops in the farmer's area, providing the data of crops in demand in that area with the help of experts and to ensure maximum profitability for farmers. This in turn can help farmers in local agriculture market growth, in production analysis and to get information about statistics of crops in their area which will help them in selection of crops to be grown in their field.

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