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Deep Learning Technique for Crop Classification to Improve Accuracy

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***Abstract*—** Agriculture is the very important sector of each country, where the gross domestic pay relies on it. Theoutcome of the agriculture or crop management was completely based on the end yield and the market rate. The complete factor of the crop yield depends on timely monitoring and suggestion .Crop classification based on high resolution satellite images are essential for supporting sustainable land management. The most challenging problems for their producing are collecting of ground based training and validation datasets. To increase the efficiency of ground data utilization it is important to develop classifiers able to be trained on the data collected in the previous seasons. In this study, we propose new deep learning method for providing crop classification maps satellite images. Main idea of the study is to utilize deep learning approach based on segmentation. Taking into account that collecting ground truth data is very time consuming and challenging task, the proposed approach allows us to avoid necessity for annual collecting of data and reducing the human efforts and resources. The research study clearly gives the idea and need of deep learning in the field of agriculture. The results were analyzed and the future perspectives were drawn with the obtained outcome.

Keywords: Deep Learning, crop classification

Satellite remote sensing is a unique source of data for the identification of crop types over large areas,as described in the last two decades in scientific literature[e.g.Ortiz et al.,1997; Pohl and Van Genderen,1998;De Wit and Clevers,2004;Ok et al.,2012;Villa et al.,2015].A number of factors influence the accuracy of satellite-based crop maps:i.e. the spatial resolution of the imagery, the classification method, and the production time horizon,i.e.the temporal extent of the dataset and phenological stages covered[Hubert- Moy et al.,2001;Van Niel and McVicar,2004;Duveiller and Defourny,2010].Cultivated crops and site characteristics regulate the selection of the most suitable satellite dataset. This paper summarizes the followings: Sect. 2 describes related work which tells about basic criteria for for crop classification using deep learning techniques. Section 3 tells how to classify crop using various deep learning techniques . Section 4 explains implementation of proposed method to satisfy our problem statement. Section 5 shows experimental analysis and results. Section 6 presents conclusion. Deep learning eliminates some of data pre-processing that is typically involved with machine learning.These algorithms can ingest and process unstructured data,like text and images,and it automates feature extraction,removing some of the dependency on human experts.Deep learning algorithms can determine which features(e.g.ears)are most important to distinguish each animal from another.In machine learning,this hierarchy of features is established manually by a human expert.

I. INTRODUCTION

Crop classification maps derived from remotely sensed data are vital for many applied tasks such as crop yield forecasting,insurance,crop are estimation and also for decision makers. One of the newest and most researched technologies nowadays is deep learning.Deep learning is a technique used to create intelligent systems as similar as possible to human brains.It has made a big impact in all types of domains such as video,audio and image processing (Wason,2018;Sharma,2019).On the other hand,agriculture is humanity's oldest and most essential activity for survival.The growth of population during the last years has led to a higher demand of agricultural products.To meet this demand without draining the environmental resources the agriculture uses,automation is being introduced into this field(Mehta,2016).The present project aims to merge both concepts by achieving autonomous weed recognition in agriculture;this goal will be reached by using new technologies such as Matlab,image processing and deep learning and Artificial Neural networks(ANN).These concepts will be explained in more detail throughout this document.Observation and assessment of crop status and development is a crucial topic for agronomic planning and management and for mitigating the effects induced by climate change and extreme events.To this aim,timely information on the area covered by different crops is necessary.

II. LITERATURE REVIEW

Basavaraj S. Anami et al[6] proposed the new technique for automate the recognition and classification of paddy crop stresses using the on field images and it has been successfully demonstrated by employing the deep learning techniques. The approach presented is applicable to 11 classes of biotic and abiotic stresses from 5 different paddy crop varieties. The best performing pre-trained deep learning model VGG-16 has been used in the classification task. The maximum average stress classification accuracy of 95.08% has been achieved using the VGG-16 by learning over 6000 images of Mugad 101 paddy crop variety. The results obtained are encouraging as the work considers more number of paddy crop stress classes and the varieties than in the reported works. But still, there is a scope for improvement. The stress classification performance of the VGG-16 model will be compared with the similar stateof-the-art models such as ResNet, GoogLeNet, Inception-v3, and LeNet as a future scope. The work carried out is challenging in terms of high irregularity in an outdoor environment. The generality of the proposed approach can make it applicable to a wide range of field crops, such as wheat, maize, barley, soybean etc. The effects of environmental conditions such as extreme temperatures and soil factors, the presence of combinatorial stresses, the quantification of stresses, and the prediction of the gap between yield potential and yield under stress can be the factors for further studies. On-time recognition and early control of the stresses in the paddy crops at the booting growth stage is the key to prevent qualitative and quantitative loss of agricultural yield.

The conventional paddy crop stress recognition and classification activities invariably rely on human experts identifying visual symptoms as a means of categorization. This process is admittedly subjective and error-prone, which in turn can lead to incorrect actions being taken in stress management decisions. The work presented in this paper aims to design a deep convolutional neural network (DCNN) framework for automatic recognition and classification of various biotic and abiotic paddy crop stresses using the field images. The work has adopted the pre-trained VGG-16 CNN model for the automatic classification of stressed paddy crop images captured during the booting growth stage. The trained models achieve an average accuracy of 92.89% on the held-out dataset, demonstrating the technical feasibility of using the deep learning approach utilizing 30,000 field images of 5 different paddy crop varieties with 12 different stress categories (including healthy/normal). The proposed work finds applications in developing the decision support systems and mobile applications for automating the field crop and resource management practices. The conventional paddy crop stress recognition and classification activities invariably rely on human experts identifying visual symptoms as a means of categorization. This process is admittedly subjective and error-prone, which in turn can lead to incorrect actions being taken in stress management decisions. The work presented in this paper aims to design a deep convolutional neural network (DCNN) framework for automatic recognition and classification of various biotic and abiotic paddy crop stresses using the field images. The work has adopted the pre-trained VGG-16 CNN model for the automatic classification of stressed paddy crop images captured during the booting growth stage. The trained models achieve an average accuracy of 92.89% on the held-out dataset, demonstrating the technical feasibility of using the deep learning approach utilizing 30,000 field images of 5 different paddy crop varieties with 12 different stress categories (including healthy/normal). The proposed work finds applications in developing the decision support systems and mobile applications for automating the field crop and resource management practices.

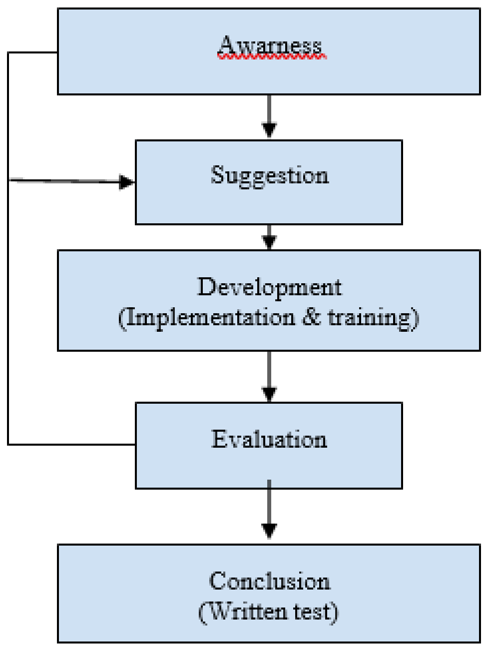
Lingjia Gu[7] proposed the feasibility and application of combination of SAR and optical data in crop classification. GF-3 data combined with polarization decomposition information, Sentinel-1SAR data and Sentinel-2 optical satellite data were used as data sources. CNN and VGG algorithms were applied as classification methods. The best overall classification accuracy was 91.6% and a kappa coefficient was 0.88, approximately. The experimental results demonstrated that using SAR data with different scattering characteristics can expand the information of optical data to a certain extent, the combination of multisource and multi-temporal data can effectively improve the classification accuracy of crops. A vast fraction of the population of India considers agriculture as its primary occupation. The production of crops plays an important role in our country. Bad quality crop production is often due to either excessive use of fertilizer or using not enough fertilizer. The proposed system of IoT and ML is enabled for soil testing using the sensors, is based on measuring and observing soil parameters. This system lowers the probability of soil degradation and helps maintain crop health. Different sensors such as soil temperature, soil moisture, pH, NPK, are used in this system for monitoring temperature, humidity, soil moisture, and soil pH along with

NPK nutrients of the soil respectively. The data sensed by these sensors is stored on the microcontroller and analyzed using machine learning algorithms like random forest based on which suggestions for the growth of the suitable crop are made. This project also has a methodology that focuses on using a convolutional neural network as a primary way of identifying if the plant is at risk of a disease or not.

III. PROPOSED WORK

Deep learning is the integral part of Artificial Intelligence (AI), where it depicts the structure of the human brain and its process. The structure of the deep learning mainly termed as neural network which is processed with the hidden layers to improve the learning. We all have a doubt why is the need of AI in agriculture because it is completely a knowledge transformation and manwork. The main reason is that the entire world is highly dependent on the biodiversity. The part of agriculture has a highest role in maintaining the biodiversity. We proposed a deep learning based system in which user will be able to upload the satellite image of the crop and get the classification out of it. The implement a different type of Crop classification system than the explained in one that makes use of an ANN to differentiate between crops

Flow Chart:



Awareness: recognition of the problem. In the current project, this step englobes the realization of the Frame ofReference and the Literature Review in order to have a deeper understanding of deep learning and choosing the most appropriate image processing techniques. This is developed by doing a research about this project's main concepts, which are robotics and automation, image processing and deep learning.

Suggestion: design and development of an idea of how the problem could be solved. This will be addressed as the development of a prototype of the program by considering the techniques chosen in the previous step. The prototype will be developed in Matlab, with the functions of downloading the images taken by th pre-processing those images and, finally, training and testing the network.

Development: when the suggestion is proved to be feasible, it is implemented depending on what kind of IT application it is. This step will lead to the final solution, and it will be divided in two parts in this project: the final programming, which will be based on the previously done prototype, and the training of the ANN to identify and classify both crops and weeds. In order to be implemented, the project will use input as pictures And then process in MATLAB

Fig: Segmentation

Evaluation: the application is examined and validated. If the solution obtained does not fulfil the expectations, it is needed to go back to Awareness or Suggestion stage. This step will be done by testing whether the computer is able to identify and classify correctly the crops and weeds. In case it isnot, the prototype done in the suggestion step would need to be modified either by changing the pre- processing techniques or the training options given to the network while programming.

Conclusion: Results and the acquired knowledge are consolidated and written. This project focuses the most on the networks performance results such as the accuracy and loss as well as the characteristics of the computer. A comparison will be made with these results.

MATLAB (an abbreviation of "MATrix LABoratory is a proprietary multi-paradigm programming language and numeric computing environment developed by MathWorks. MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages.

Although MATLAB is intended primarily for numeric computing, an optional toolbox uses the MuPAD symbolic engine allowing access to symbolic computing abilities. An additional package, Simulink, adds graphical multi-domain simulation and model-based design for dynamic and embedded systems.

The basic data structure in MATLAB® is the *array*, an ordered set of real or complex elements. This object is naturally suited to the representation of *images*, real-valued ordered sets of color or intensity data.

MATLAB stores most images as two-dimensional matrices, in which each element of the matrix corresponds to a single discrete *pixel* in the displayed image. (Pixel is derived from *picture element* and usually denotes a single dot on a computer display.) For example, an image composed of 200 rows and 300 columns of different colored dots would be stored in MATLAB as a 200-by-300 matrix.

Some images, such as truecolor images, represent images using a three-dimensional array. In truecolor images, the first plane in the third dimension represents the red pixel intensities, the second plane represents the green pixel intensities, and the third plane represents the blue pixel intensities.

This convention makes working with images in MATLAB similar to working with any other type of numeric data, and makes the full power of MATLAB available for image processing applications. For more information on how Image Processing Toolbox™ assigns pixel indices and how to relate pixel indices to continuous spatial coordinates, see Image Coordinate Systems.

Deep Learning can be viewed as a result of the natural evolution of information technology. An evolutionary path has been witnessed in the database industry in the development of the following functionalities: data collection and database creation, data management (including data storage and retrieval, and database transaction processing), and data analysis and understanding (involving data warehousing and Deep Learning). For instance, the early development of data collection and database creation mechanisms served as a prerequisite for later development of effective mechanisms for data storage and retrieval, and query and transaction processing. With numerous database systems offering query and transaction processing as common practice, data analysis and understanding has naturally become the next target.

Classification has delivered important meanings in our life. In general, the definition of classification simply means the grouping together of alike things according to common qualities or characteristics. Classification has essential part to play especially in assisting in the search process. By classifying things into different segments it enables us to retrieve things or information that we needed to look for, without the risk of too much time consuming in retrieving that particular things or information.

Classification used as a tool for very simple yet infinitely crucial purpose. Its purpose is to secure an order which will be useful to readers and to those who seek information with the smallest complication of search, also known as a technique designed to expedite the full use of the knowledge stored in books and other material housed in the collection.

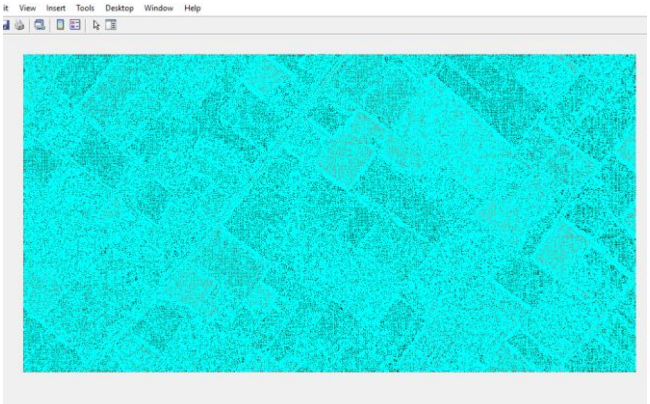
Objective:

1.To develop a system that will be very beneficial for farmers, Processing Company, distributors, retailers and customers
2.The analysis of the classification techniques of deep learning
3.To implement deep learning techniques for crop classification
4.To develop a system for crop classification Comparative study of the classification techniques to analyze performance.

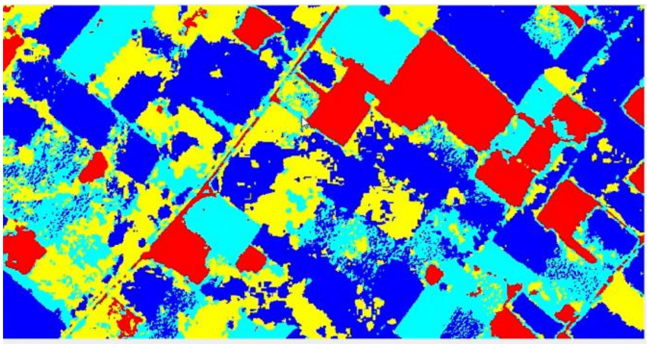
IV. RESULTS

The execution details of whole system that is how the system works by graphically. Graphically, all the control flow is showing with the help of screenshots and images so as to easily understand the working of system is shown below

Input Image

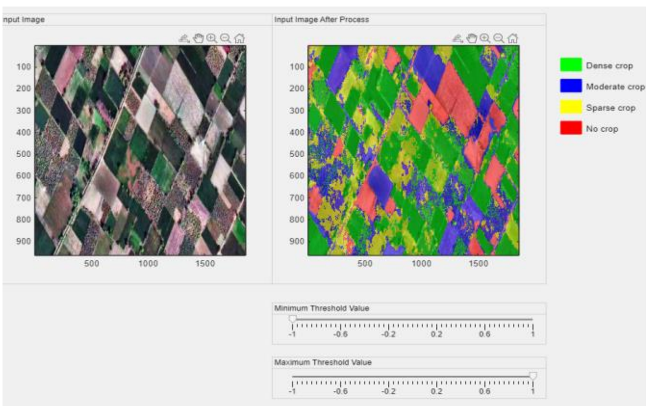


Level 1 image processing



Level 2 image processing

Level 3 image processing



Final Output Image

V. CONCLUSION

Satellite monitoring capabilities are essential to understand large scale environmental changes affecting climate, biodiversity and humans. Vast resources have been invested in satellite development, launch and product creation, and thousands of articles have evaluated image classification methods for producing land-cover maps. To date the results of these studies have not been synthesized to generate conclusive guidelines for selecting a land-cover classification process. Our work bridges this gap via a meta-analysis of peer-reviewed studies to statistically quantify improvement in accuracy achieved by different input data enhancements and classification algorithm choices. By identifying the current state-of-the-art, we provide pragmatic guidance, derived from years of published research, aiming to accelerate future processing and algorithmic developments that will yield further improvements in land-cover classification accuracy.

The main practical application of our results is to help researchers decide which improvement methods are most promising. Researchers can prioritize their efforts by obtaining a clearer idea of expected improvements achieved by different methods. The highest improvement resulted from inclusion of texture with a mean increase in overall accuracy. The increase in overall accuracy achieved by including texture is attributed to the additional spatial context information provided. These easy to compute texture metrics should be a primary consideration for image classification of land cover . It showed that crop types could be identified by deep learning features in Sentinel-2 dense time series images with missing information due to clouds or cloud shadows randomly, which avoided spending extra time on missing information reconstruction. In the future, the networks can be extended to two dimensions to complete the semantic segmentation of time series images with missing values.

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