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A novel method to maximize the farm resources using Mask - RNN based algorithm

Nishad Gupta
Sat Paul Mittal School
Ludhiana
Nishad162005@gmail.com

Reetu Jain
Chief-Mentor and Founder of On My Own Technology Private Limited Mumbai,
reetu.jain@onmyowntechnology.com

Abstract: *In this paper, we propose the use of satellite imagery for capturing crop yield variability at the field scale. The objective of the research is to study the spectral reflectance of the plant changes over time and estimate the water and nutrients required in the given patch of land. An improved Mask R-CNN (region-based convolutional neural network) model is proposed for field NDVI image segmentation, the purpose of the study is to support farmers by optimizing their resources and increasing the yield, the output of the segmented mask is integrated with the smart irrigation control system to facilitate the optimized supply of water depending on the amount of nutrient deficient part of the field. The study of the Mask R CNN framework can segment the nutrient-deficient part of the field with an accuracy of 74%.*

Keywords: **Mask R-CNN, NDVI, Agriculture, Deep Learning, Image Segmentation.**

1. Introduction

The world food demand is going to increase in the next 50 years, it is estimated that the food demand will increase by 60% by 2050 [1], to meet the demand agriculture output needs to increase and use the resource efficiently, Remote sensing has the promising technology that can be used to detect the land cover and the use. Low-distance sensing methods are applied in agriculture or breeding research to identify the crop genotype and adapt to certain environmental conditions. [2] Remote detection and performance evaluation of major crops are important tools for precision agriculture, agriculture and decision-makers.

Crop performance is mainly affected by an environmental conditions such as water and nutrient availability, the temperature during the growing season, soil conditions and crop management [3], the crop performance can be measured as the biomass or yield at the end of the season, During the growing season crop vitality is often characterized by traits such as growth, leaf greenness, leaf area index (LAI), canopy cover (CC), leaf water content (LWC) and leaf chlorophyll content. Many of such traits can be remotely sensed by means of spectral indices. Leaf greenness and plant biomass is often estimated using the normalized difference vegetation index (NDVI)

There are two kinds of platform for remote sensing: satellite and the drone, the satellite has the advantage that it can observe a wide area, on other hand, the drone has the advantage of capturing the high-resolution image with lower height and is independent of the weather [4]

We introduce the algorithm that given the NDVI satellite image can distinguish the crop field with a patch of crop that is nutrient deficient and the patch of crop that is good so the nutrient, fertilizer and water can be effectively used for the bad patch of the land.

The introduction of new agricultural techniques over the past century has helped agriculture keep pace with the growing demands for food and other agricultural products. However, further increases in food demand, a growing population, and rising income levels are likely to put an additional constraint on natural resources. Consequently, the excessive water used in agriculture needs to be managed efficiently in order to control the negative consequences. Emerging technologies could be utilized to perform informed management decisions. This paper presents how image processing can be used in Precision Farming to optimize agricultural inputs to increase agricultural production and reduce output losses. By collecting high-resolution satellite images and correlating the Normalized Difference Vegetation Index, we designed a model to predict the water requirements of a crop and therefore, stimulate the drip irrigation system accordingly.

2. Literature Review

Agriculture is a prime source of food production. As the world population increases exponentially, it will surely lead to a surge in food demand in the near future. Considering the fact that we have limited availability of land and water, it becomes very important to use both resources efficiently. Every crop has different requirements in terms of water and type of soil. It is also observed that water content within the same crop on the same farmland also shows variations and these variations can be used in order to utilize water efficiently.

According to a study done by [1], it is observed that 70% of the water withdrawal accounts for farming and this number rises up to 95% for some developing countries. Extreme weather conditions have led to an increase in crop water demand and at the same time it has posed the possible threat of water scarcity.

In [2] a multispectral imaging system is implemented to calculate Normalized Difference Vegetation Index(NDVI) with the help of a dual camera system mounted on an Unmanned Aerial System. NDVI is calculated by comparing IR radiation and red light radiation emitted by plants. The lower value of NDVI indicates a deficit of water in plants. This prototype is implemented with the help of two camera systems mounted on a Quadrotor. A trigger system is designed with the help of a microcomputer to activate the camera from time to time at a given distance. Images are processed to generate orthomosaics after collecting overflight and NDVI is calculated to post that. NDVI can be calculated using the equation given below

$$NDVI = \frac{p_{nir} - p_{red}}{p_{nir} + p_{red}}$$

In [3] a vision-based high throughput system is implemented to identify and detect stress caused by water deficit in maize plants. It uses a combined approach of infrared imaging and image processing to distinguish between well-watered maize plants and the one with a water deficit. To achieve this a gantry system is designed which moves two carts with help of stepper motors in vertical and horizontal directions respectively. The pi-Camera (NIR-Green-Blue), which moves in the vertical direction and uses a total of 800 images, is scanned for over 30 minutes in a room which was illuminated with a source of normal and IR light. These images are in [processed to average and finally, NDVI is calculated to determine water content

In[4], with the help of RGB and NIR bands, low altitude images obtained with IR sensing are processed to calculate vegetation index. This approach uses texture along with colorsET. processing and calculating NDVI and further classifying images with the help of a support vector machine RBF classifier (SVM). For the classification of Haralic and BIC, features are extracted. This method demonstrated the accuracy of 90.6 % for eucalyptus and 80.7 per cent for sugarcane crops. Along with classification it also provides estimation data for plantations.

In [5], Near Infra EvapoTranspiration is combined with Principal Component Analysis to classify different types of dried medical leaves. XDS Opti probe analyzer from the FOSS NIR system was used to analyze spectral signature by calcusoonion index of energy reflected by plants.

It is also possible to detect infection with the help of NIR spectroscopy. As demonstrated in [6], SVM neural networks with polynomial and radial bases can be used to classify infected and non-infected plants and the same data can be used to make efficient use of water for irrigation

As the climate is also critical for water usage, In [7] analysis is done with the help of Mapping evapotranspiration with High-Resolution Calibration (METRIC) model which solves analysis of water usage over the selected area under observation. The METRIC model uses Landsat TM data, (both reflected and thermal), by computing a complete energy balance for each pixel and it computes and maps ET. Data input to METRIC includes wind speed, solar radiation, dew point temperature, air temperature, and reference ET. METRIC computes fluxes of sensible heat and ET. This method maps Evapotranspiration with help of thermal and reflected waves. This analysis is typically helpful, especially in evaluating geographical usage and requirements of water for farming.

3. Irrigation Strategies:
The water balance method of irrigation keeps track of the soil water deficit by accounting for all inflows and outflows of water. In essence, this approach aims to maintain the soil's water balance by replacing any water that has been lost. A diagrammatic representation of replacing of soli water is shown in figure 1.

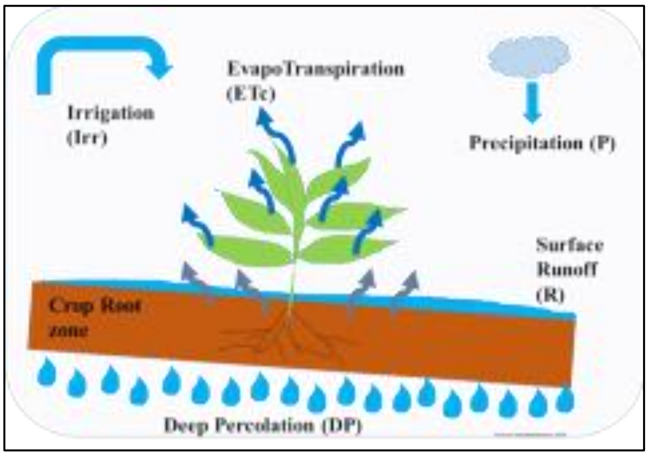


Figure 1: Diagrammatic representation of replacing of soli water

The water balance method of irrigation keeps track of the soil water deficit by accounting for all inflows and outflows of water. In essence, this approach aims to maintain the soil's water balance by replacing any water that has been lost, deficit irrigation does not occur in the soil. Since the water balance model additionally takes into account meteorological information like temperature, precipitation, and reference evapotranspiration, it is more useful for irrigation planning than simply monitoring soil moisture to predict irrigation volume. The water balance model can determine the future soil water balance and anticipate how much irrigation will be required in the future given future weather predictions. This is crucial for figuring out irrigation scheduling for the entire season

4. Background and motivation:

Food production depends heavily on agriculture. But as the population of the globe grows, so does the need for more output. The only way we can satisfy these needs, given the amount of arable land, is by increasing the usage of agricultural inputs, such as fertilizers, pesticides, water, and other inputs. Both significant contributors to and a victim of water scarcity, and agriculture. Nearly 70% of all water withdrawals are used for agriculture, and in certain developing nations, this percentage might reach 95%. As the population expands, so does the need for water resources, and this intensification of agricultural inputs contributes to environmental damage such as eutrophication, groundwater depletion, and diminished surface flows. The development of strategies that boost agricultural output through improved input usage efficiency and decreased environmental losses is necessary for an ecologically sustainable production system. One of the essential elements of a sustainable agricultural system is precision agriculture, which entails resource management via the use of cutting-edge communication, information, and data analysis methods. Farmers are now able to identify geographical variability (such as soils) among farms and vast crop fields that have an adverse impact on crop growth and yields. By collecting significant amounts of spectral data from wireless sensor networks, their remote sensing systems stop the loss of water or nutrients. Then, to extract meaningful data from that massive data set, methods like big data analysis, artificial intelligence, and machine learning are used. Techniques like big data analysis, artificial intelligence, and machine learning are then utilized to draw useful information from that large volume of data. In the past most of the studies have focused on various soil properties such as evapotranspiration estimation and pest management, this paper presents research we conducted on collecting high-resolution images from satellites and differentiating patches of the agricultural field on the basis of crop water requirements using a python programming language. The factor evapotranspiration was calculated and thereby the NDVI was calculated. The Natural Differentiation Vegetation Index was then correlated with the crop water requirements. We also proposed an additional system of mechanical pumps wherein they will be stimulated according to the crop water requirements of a particular patch. Thus, minimizing water wastage and saving plants from weltering. [5]

5. Proposed Methodology:

The data is collected from the website, the data contains NDVI images and the RGB satellite images and the mask. The proposed method is to normalize the images and make all the images of standard size. The image data set contains the mask, therefore to segment crop boundaries with the good crop yield and bad crop yield we are using the Mask R CNN deep learning algorithm. Once we have the segmented image, we can classify which part of the field requires more watering, nutrients and fertilizer.

5.1. **Machine learning model**

To segment the picture, we are utilizing the mask RNN. The notion behind the mask R-CNN is straightforward: faster R-CNN already produces a class label and a bounding-box offset for each potential item; we just add a third branch that outputs the object mask. Thus, mask R-CNN is a logical and reasonable concept. The additional mask output, however, differs from the class and box outputs and necessitates the extraction of an object's considerably more precise spatial organisation. After that, we go into Mask R-essential CNN's components, including pixel-to-pixel alignment, which is the fundamental component that Fast/Faster R-CNN lacks [6].

Mask R-CNN adopts the same two-stage procedure, with an identical first stage (which is RPN). In the second stage, in parallel to predicting the class and box offset, Mask R-CNN also outputs a binary mask for each RoI. This is in contrast to most recent systems, where classification depends on mask predictions. Our approach follows the spirit of Fast R-CNN [6] that applies bounding-box classification and regression in parallel (which turned out to largely simplify the multi-stage pipeline of original R-CNN [10]). Formally, during training, we define a multi-task loss on each sampled RoI as L = Lcls + Lbox + Lmask. The classification loss Lcls and bounding-box loss Lbox are identical to those defined in [6]. The mask branch has a Km2- dimensional output for each RoI, which encodes K binary masks of resolution m × m, one for each of the K classes. To this, we apply a per-pixel sigmoid and define Lmask as the average binary cross-entropy loss. For an RoI associated with ground-truth class k, Lmask is only defined on the kth mask (other mask outputs do not contribute to the loss). According to our definition of Lmask, the network may produce masks for each class without there being any rivalry between them; instead, we rely on the specialized classification branch to forecast the class label that will be used to choose the output mask. This separates class prediction and the mask. Contrary to conventional wisdom, semantic segmentation with FCNs often employs a multinomial cross-entropy loss and a per-pixel softmax. In that instance, masks across classes compete; in our case, with a per-pixel sigmoid and a binary loss, they do not. By means of tests, we show by experiments that this formulation is key for good instance segmentation results.

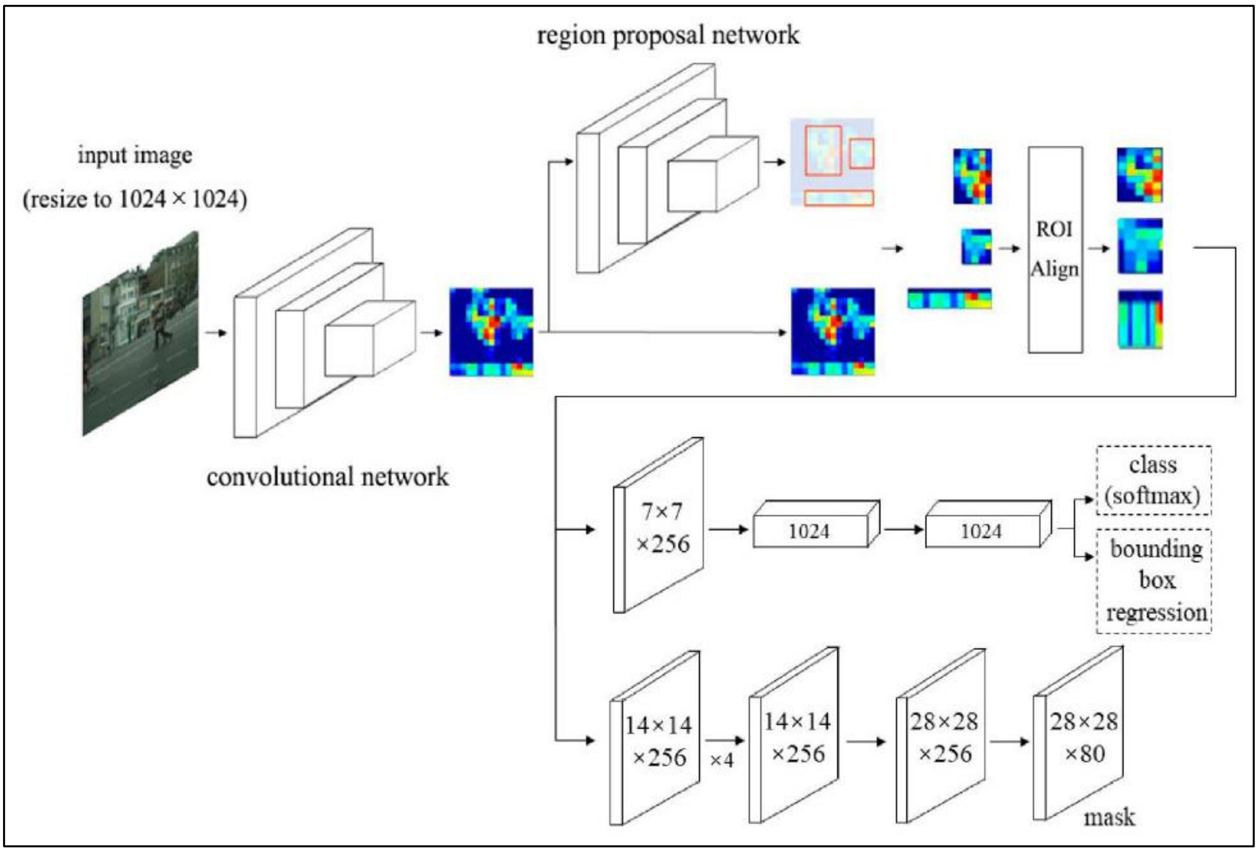
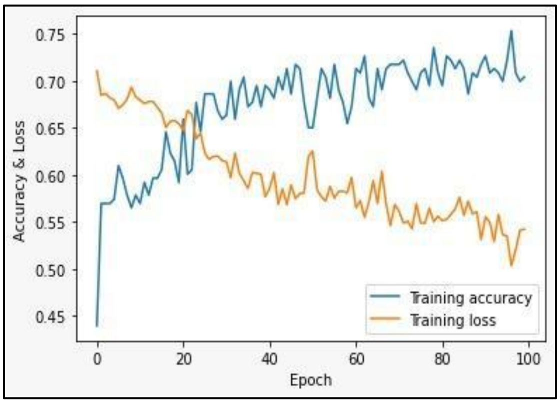


Figure 2: The representation of the Mask RCNN

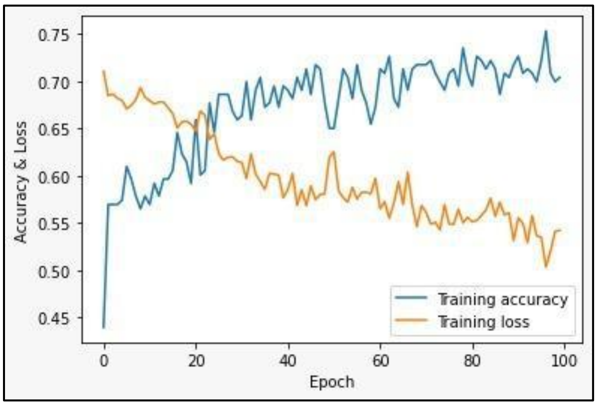
6. **Results and Discussions**

In this section of the paper, the results obtained after applying the methodology to the problem under consideration is discussed in brief.

6.1. Results



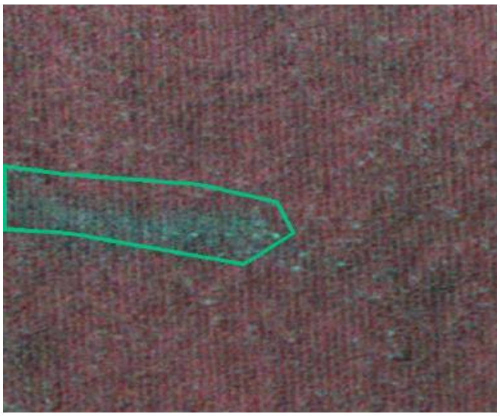
(a)



(b)

Figure 3: The (a) training and (b) testing accuracy and loss graphs

We classified the data randomly at 70% as the training data set and 30% validation test, the mask R-CNN framework achieved 74% accuracy, and the loss curve for training and the validation is shown below.



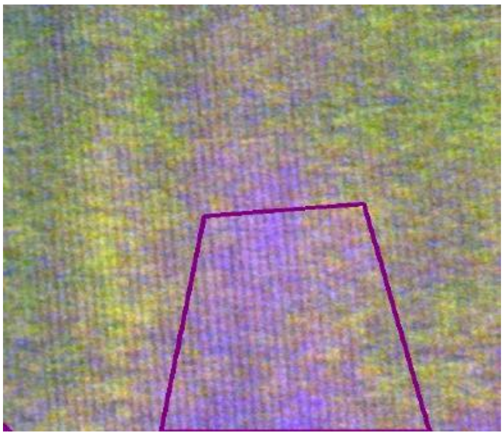


Figure 4: Field with nutrient deficit

The above figure shows the fields with the nutrient-deficient section of the field properly detected, although the proposed method can achieve encouraging performance, there are still some shortcomings. Examples of false detection and missed detection segments are shown below, where even the NDVI image with the water body is detected as nutrient deficient.

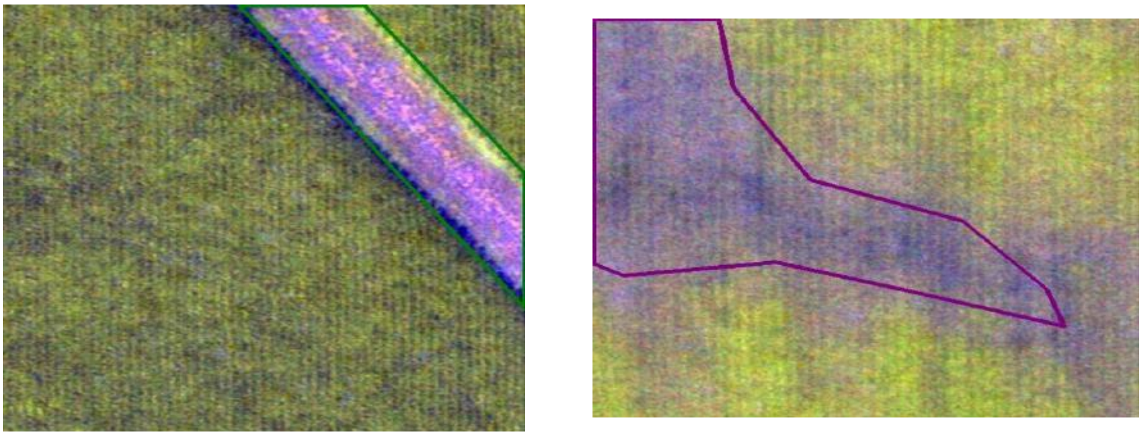


Figure 5: False detection and missed detection segments

6.2. Discussion:

Crop water requirements are the total amount of water, independent of source, required for typical crop development and output across time and space. This water may be provided by precipitation, irrigation, or a combination of both.

Water is required primarily to fulfil the demands of evaporation (E), transpiration (T), and metabolic needs of plants, which are together referred to as consumptive usage (CU). Because water consumed in plant metabolic processes is insignificant, accounting for less than one per cent of total water moving through the plant, evaporation (E) and transpiration (T), i.e. ET, are directly regarded to be equivalent to consumptive use (CU). In addition to ET, water demand (WR) comprises irrigation water losses (percolation, seepage, and runoff) and water required for specific operations such as land preparation, transplanting, leaching, etc. The total water requirement can be represented by the following equation

$$WR = CU + \text{application losses} + \text{water needed for special operations.}$$

Water for Irrigation requirement is the total quantity of water applied to the land in supplement to the water supplied through rainfall addition to the soil profile to meet the water need for the crop for optimum growth that can be given by the formula

$$IR = WR-(ER+S)$$

So having the same irrigation profile for the whole crop field is not optimal, and there might be a patch in the file that may require more or less water. The trained segmented model can be integra**ted** with smart irrigation control systems irrigation systems to facilitate the autonomous optimal supply of water calculation and this system will ensure a proportionate supply of water depending on the amount of nutrient deficient part of the field.

7. Conclusion and Future Scope

In this paper, we present the Mask R-CNN segmentation for the agriculture domain that is able to segment the image in the crops with good yield and the crop with nutrient deficiency, the segmented output is used to determine the optimal use of the agricultural resource such as water, fertilizers and nutrients. Additionally, extensive training on the data set demonstrates the effectiveness of the proposed framework.

Since it is time-consuming and laborious to label field images as well creating the mask we will try the semi-supervised and weakly supervised segmentation technique in future, The post-data processing after segmentation can help to understand the area of the affected field, and the suggestion can be made based on the area to set up proper irrigation techniques and the proper use of fertilizers, the same algorithm can be extended to the drone-based monitoring system.

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Data repository

The data used to support the findings of this study are available from the corresponding author upon request.

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