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Evaluating Soybean Root Health Using Residual Neural Network (ReNN) Based Image Analysis

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ABSTRACT

ReNN's layer-wise image segmentation and robust data processing address the complexities of soybean root analysis, providing valuable insights for improved crop management. Accurate assessment of soybean root health is crucial for optimal crop production and growth. This study utilizes Residual Neural Network (ReNN) image evaluation to analyze soybean root development. Field data is collected and integrated by deploying sensor-based devices (IoT Devices) to evaluate soybean crop stages. ReNN facilitates data preprocessing, layer-wise image segmentation, and effective data processing, enabling accurate assessment of root health, plant vigor, flower fragmentation, and fruit formation. This approach predicts soybean crop yield and provides valuable insights into degradation detection and decision-making for optimal soybean cultivation practices. ReNN utilizes layer-based image formation, collecting data from farm fields through sensor-based devices. The dataset encompasses various environmental and weather conditions, ensuring comprehensive coverage. Key considerations for data preprocessing include temperature, humidity, precipitation as the Weather conditions, soil type, moisture, sunlight as Environmental factors, field location, soil heterogeneity as Spatial variability, and growth stage, seasonality as Temporal variability. By integrating these factors, ReNN enables accurate evaluation of soybean root conditions, facilitating root health assessment, Plant growth monitoring, Yield prediction, and optimized cultivation practices.

INTRODUCTION

In the realm of technological approaches, the domain of agriculture is vast and plays a significant role in the advancement of agricultural technology. The approaches used were used to evaluate the data set of images. The images are clear with proper originality and appropriate for evaluation. Therefore, the technological enhancement toward the uses of artificial intelligence and its based method for the image evaluations for the soybean crop farming. Technologically, the devices deployed for the image extractions and the images of the plant picked from the field and images are further forwarded for the input values. Image recognition in agriculture has promoted research for the increase in the production of the crop. Additionally, crop evaluation research facilitates the identification of the health condition of the crop plant. The system that the paper shows focus on the design of the device and the adoption of the best method based on artificial intelligence for the validation of image-based data sets. The approaches of Residual Neural Network (RNN) are suitable for proper validation of the image-based dataset. Here, the research engaged the IoT-based image cameras that study and evaluate data sets of files and input the values of the RNN method of evaluation of the crop conditions. As research supports, the ideology is extracted based on technical devices that support the states of the root formation and condition of the soybean plant in the farming of soybeans (He, 2016).

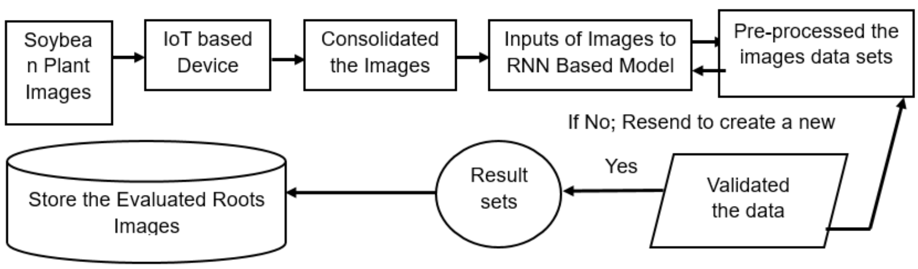

Figure 1: Model of the Evaluating the Soybean Plants and Roots Images Analysis

LITERATURE REVIEWS

The Literature review considers the two states of image segmentation, the first is considered which is based on computer vision and the states of images. The second is based on the model of IoT controllers that illustrates the image processing for the segmentation and is forwarded

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to the machine learning-based model of the imaging system is ResNN (Krizhevsky, 2017).
Based on Computer Vision Techniques:
Computer vision technology can be used in agriculture to help farmers monitor crops, detect pests and diseases, and improve yields:

Crop Monitoring
High-resolution cameras and algorithms can analyze images of crops to provide insights into plant health, growth stages, and potential yield.

Pest and Disease Detection
Computer vision systems can help identify potential pests and diseases that may cause crop losses.

Weed Identification
Computer vision can help identify weeds and apply precision herbicides.

Yield Prediction
By analysing factors like plant height, leaf area, and fruit count, computer vision can help predict crop yield.

Automated Harvesting
Computer vision can help automate the process of harvesting crops.

Soil Analysis
Computer vision can help analyze soil conditions.

Nutrient Management
Computer vision can help identify nutrient deficiencies and apply targeted fertilizers.
Computer vision can be used in a variety of ways, including: (Leibe *et al.*, 2016)

1. UAVs: Unmanned aerial vehicles (UAVs) equipped with computer vision systems can help farmers monitor crops and assess plant health.
2. Mobile robots: Farmers can use mobile robots equipped with computer vision to drive around and collect data.
3. Static cameras: Farmers can use static cameras to take images of crops from an advantageous position.

The Authors Suggested that, Based on Data Availability Image Quality
Many studies and competitions used plant image datasets with a single background. For example, the Plant Village dataset contains many labelled plants leaf images from various species with different diseases, but the pictures were from a controlled environment, and their backgrounds are very simple. However, because of lighting, occlusion, and shadows in the natural atmosphere, the image quality and visual perception ability will degenerate greatly. Many noises appear in the images, which is a big challenge for automatically analysing unconstrained natural images in the field. Although human visual systems can easily deal with these problems, establishing a computational model of plant phenotyping is still an open-ended question (Hu *et al.*, 2018).

Image Annotation
Deep learning needs to learn features from sufficient annotated data, but data annotation faces the following challenges:

a. Manual annotation sometimes requires a large amount of prior or professional domain knowledge and rich working experience.

b. Data annotation is a time-consuming and hectic step, especially in object detection and image segmentation. Detection and segmentation require instance-level (boxes) and pixel-level annotations (masks). If more and more images are to be annotated, the workload will be massive, while efficiency and accuracy cannot be guaranteed (Lin *et al.*, 2019).

c. Some images lack visual cues, such as hyperspectral and thermal imaging, so it is much more difficult to label these data than RGB images.

Online researchers have deployed a human-machine collaboration interface called fluid annotation (Andriluka *et al.,* 2018) that can be used to annotate the class label and delineate the contours of every object and background in an image (Bello *et al.*, 2019).

The Authors Suggested the Data-Based Analysis Algorithm Robustness
At present, some mainstream algorithms perform well on particular datasets, and most of them are only designed for specific organs or specific plant species. Due to the large differences in colour, shape, size, and other characteristics between different detection objects, these algorithms do not generalize well. When the dataset changes, many algorithms will be invalid, so researchers must redesign the feature extractor and readjust the hyperparameters. For stress phenotyping, the degree of plant stress changes over time. The model needs to be improved and modified to be dynamically analysed throughout the entire cycle of stress, which is a challenge for designing a processing framework (Li *et al.*, 2018).

Deep Learning
Firstly, deep learning-based algorithms rely on a big number of labelled sample images, which makes it difficult to achieve excellent results in the following three scenarios:

• Training samples do not exist in some object categories.
• There are a few samples in object categories.
• The sample size of different categories is extremely imbalanced. Then, some deep learning-based solutions lack prior knowledge, and it is difficult to adaptively use my discriminative visual features. Moreover, the deep neural network is used as a “black box”, which cannot perform explicit reasoning and lacks interpretability. Tasks like gene-phenotype association and image description require high-level logical reasoning and often can’t be solved with simple classification or regression methods.

These problems need more advanced approaches, such as: Deep learning model, Multimodal learning, Graph-based methods (Zagoruyko *et al.*, 2017).

Finally, most 3D point clouds are still analysed by utilizing traditional 3D processing methods. Solutions based on deep learning have not been popularized in plant phenotyping. The following research aspects are worthy of attention in the future.

1. Plant images with complex backgrounds require effective segmentation of the foreground and background. Methods based on deep learning are very suitable for image segmentation, but image annotation becomes the major limiting factor for applying deep learning in plant phenotyping. To reduce the requirements of annotated data, the following solutions were proposed and developed: On the one hand, some image generation strategies (e.g., GANs) can be applied to increase image diversity and availability. On the other hand, the dependence of models on data can be reduced by improving algorithms, such as zero sample learning, small sample learning, transfer learning, and so on (Tan & Le, 2019).
2. Most existing deep learning algorithms rely on many labelled images to fit many parameters for prediction, ignoring the prior knowledge of many domain associations and the intuitive understanding of decision-making processes, which limits the interpretation of model functions to a certain extent (Pharm, 2020).
3. CNN has great potential in 3D reconstruction and segmentation. Some approaches use CNN to project 2D segments onto 3D representations or apply them to 3D images directly. Thus, a lot of 3D processing work requires to application of CNN architectures to characterize and understand plant phenotypes directly

Model of IOT devices for Image Extraction

The author suggested that the rapid evolution of IoT devices necessitates efficient image super-resolution techniques, while existing advanced methods, based on deep convolutional neural networks, are too resource-intensive for these circuit-based models, and this gap illustrates the need for a more suitable solution. In this study, we introduce a lightweight, essentially super-resolution model specially designed for IoT devices. This model incorporates a novel deep residual feature distillation block (DRFDB), which leverages a depth-wise-separable convolution block (DCB) for effective feature extraction. Determined to reduce computational and memory demands without changes to image quality. The model shows improved performance metrics like PSNR, while requiring fewer parameters and less memory usage, making it highly suitable for IoT applications. This study presents a breakthrough in super-resolution for IoT devices, balancing high-quality image reconstruction with the limited resources of these devices (Gao *et al.*, 2019).

MATERIALS AND METHODS

ResNN is an artificial Intelligence method to help in the evaluation of the images of the plant soybean crop. A Residual Neural Network (ResNet) stacks residual blocks on top of each other to form a network.

The Residual Neural Network

To know about residual neural networks and the most popular ResNets, including ResNet-34, ResNet-50, and ResNet-101. In current years, the field of artificial intelligence applied to computer vision has undergone far-reaching transformations due to the introduction of new technologies (Xie S, Zerhouni E, Huang G, 2017).

a. The rapid progress in deep learning has enabled computer vision models to achieve unprecedented levels of accuracy and efficiency in tasks such as image recognition, object detection, and face recognition, surpassing human capabilities in many cases.

b. But, while it gives us the option of adding more fully connected layers to the CNNs to solve more complicated tasks in computer vision, it comes with its own set of issues. It has been observed that training the NN becomes more difficult with the extension in the number of added layers, and in some cases, the accuracy dwindles as well.

c. It is here that the use of ResNet assumes importance. Deeper neural networks are tough to train. With ResNet, it becomes easy to surpass the difficulties of training very deep neural networks.

d. When working with deep convolutional neural networks to break a problem related to computer vision, machine learning experts engage in mounding further layers. These fresh layers help break down complex problems more efficiently, as the different layers can be trained for varying tasks to get largely accurate results.

e. While the number of piled layers can enrich the features of the model, a deeper network can show the issue of declination. Basically, as the number of layers of the neural network increases, the complexity of situations may get impregnated and sluggishly degrade after a point. As a result, the performance of the model deteriorates both on the training and testing data.

f. This declination isn't a result of overfitting. Rather, it may affect the initialization of the network, optimization function, or, more importantly, the problem of evaporating or exploding slant

Various Factors Based on Types of Resnet Are as Follows

ResNet-50 Architecture: Bottleneck Design

ResNet-50 uses a bottleneck design, which reduces the number of parameters and computational cost. 3-layer blocks: ResNet-50 uses a stack of 3 layers instead of the earlier 2-layer blocks, forming a 3-layer bottleneck block. Higher accuracy: ResNet-50 achieves much higher accuracy than the 34-layer ResNet model. Performance: The 50-layer ResNet-50 achieves a performance of 3.8 billion FLOPS.

ResNet-101 and ResNet-152 Architecture: Large Residual Networks

ResNet-101 and ResNet-152 are constructed using more than 3-layer blocks, enabling deeper networks with lower complexity. Lower complexity: Despite increased network depth, the 152-layer ResNet has much lower complexity (11.3 billion FLOPS) than VGG-16 or VGG-19 nets (15.3/19.6 billion FLOPS).

ResNet-50 with Keras: Keras API

Keras is a popular deep learning API known for its simplicity and ease of use. Pre-trained models: Keras comes with several pre-trained models, including ResNet-50, which can be used for various experiments and applications.

Technical Approaches for Validation of the Soybean Plant and the Condition of Its Roots

The technology of computer vision and the integration of the model of ResNet is being applied to the farming of soybean crops. The adjustment design for the evaluation supports and recognizes the image data sets and validates the progress of the soybean plants. Recommended the IoT and ResNet model based on a computer vision system is as below block diagram, where the camera is built for extracting the images, and after those images are forwarded to the memory shuttle of memory, which is built into the circuit of IoT devices. The memory transferring the images to the computer system, where an algorithm extracts the image-based data of the sets that are recognized for the image segmentation. The Block Diagram shows the stepwise uses of the IOT model and the process of input values. The block diagram also integrates the steps of preprocessing with the help of modules of ResNN (Simonyan & Zisserman, 2014; Szegedy *et al.*, 2015).

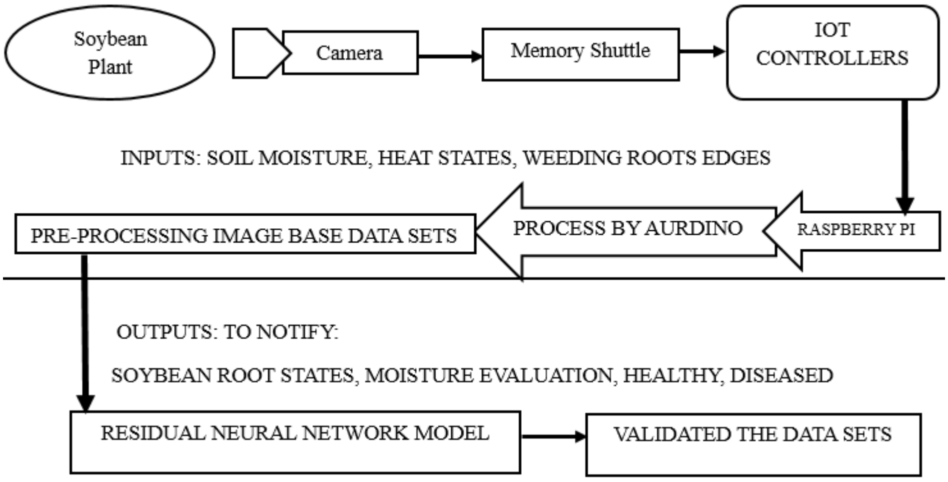


Figure 2: Model-Based to define the IOT and ResNN for Validating Data Set

RESULT AND DISCUSSION

Evaluation And Analysis Of Soybean Roots Using Resnn

Technology ReNN Architecture Consists of Residual Block

Residual blocks are the main components of the Residual Neural Network. In a classical neural network, the input is transformed by a set of convolutional layers then it is passed to the activation function. In a residual network, the input to the block is added to the output of the block, creating a residual connection. The output of the residual block H(xi) can be represented by:

$H(xi) = F(xi) + xi$

F(xi) represents the residual mapping learned by the network. The presence of the identity term x allows the gradient to flow more easily.

S Connection

S connection is a Skip connection that helps in forming the residual blocks. Skip connection consists of the input of the residual block that is bypassed over the convolutional layer and added to the output of the residual block.

ST Layers

ResNet architectures are formed by stacking multiple residual blocks together. Using these multiple residual blocks together, resnet architecture can be built very deep. Versions of ResNet with 50,101,152 layers were introduced.

Global Average Pooling(GAP)

Resnet architectures typically utilize Global Average Pooling as the final layer before the fully connected layer. GAP reduces spatial dimensions to a single value per feature map, providing a compact representation of the entire feature map (Zhang *et al.*, 2019).

Healthy soybean roots have the following characteristics (Chen *et al.*, 2020)

- Depth: Soybean roots typically grow to a depth of 2–3 feet, but most of the roots are in the top 6–12 inches of soil.
- Nodules: A healthy soybean plant should have 6–20 large nodules on the main tap root and smaller nodules on the auxiliary roots. Nodules are formed by bacteria in the soil and provide much of the plant's nitrogen supply.

• Colour: A healthy nodule is red or pink, which indicates active nitrogen fixation. A white or gray nodule is immature and should be checked again in a week. A green, brown, or mushy nodule is dead.

• Root type: Soybeans have both deep, vertical roots and shallow, lateral roots. The deep roots access water from deeper soil layers, while the shallow roots increase the plant's ability to absorb nutrients from the topsoil.

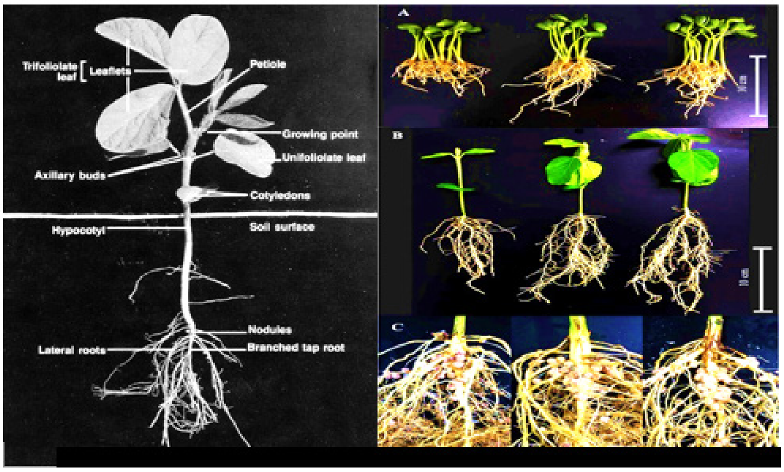
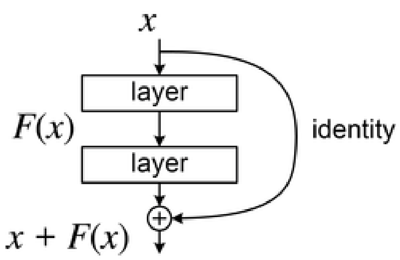


Figure 3: Images of Standardized Formation of Soybean Plant

ReNN Model for Evaluation and Image-Based Analysis



Y (output) = x+F(x)

Considering,
Farming Side s1: Images Inputs Ms : Length T1 : Root size R_Lat, R_Nod, R_Bra
In the process of ResNN, the extraction of images is consolidated from the M1 position to the Ms position. After that, the land-side-wise extraction is in observation for the same, considering the s1 to s nth side. Whereas the root observation key points are evaluated and analyzed to add f(x) = T1+R_Lat, similarly add f(y)= T1+R_Nod and f(z)= T1+R_Bra.
The functions f(x) = partially integrated mapping and putting the evaluation steps for States Lateral Roots, States Nodules, and States Branchtop root.
Therefore, Output Evaluation y = f(x) +f(y)+f(z)
Same way, the changes in image observation, the values are integrated, and the analysis of the present image data set would be responsible for the analysis of the healthy condition of the roots, and also changes in the image data set to observe the desired diseases and progress of the plant.

CONCLUSION

The Observation implementation is still in process for the effective and productive extraction of the root image, so the progress and evaluation of the roots help and are more supportive of the progress of the plant. That plant's progress directly raises the production of the soybean.
Here are illustrated the key facts for ResNN, which is supportive of the evaluation of the soybean plants in the future study and project of IoT deployments.

• ResNets (Residual Networks) are a variant of deep learning algorithms that are particularly for image recognition and processing tasks. ResNets are known for their make to train very deep networks without overfitting

• ResNets are helpful for detection tasks. Key point detection is the task of locating points on an object in an image. For example, detection can be used to locate the eyes, nose, and mouth on a human face.

• ResNets are well-suited because they can learn to extract from images at different scales.

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