Smart Plant Disorder Identification using Computer Vision Technology

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Abstract— **The soil composition around the world is depleting at a rapid rate due to overexploitation by the unsustainable use of fertilizers. Streamlining the availability of nutrient deficiency and fertilizer related knowledge among impoverished farming communities would promoter environmentally and scientifically sustainable farming practices. Thus, contributing to several Sustainable Development Goals set out by the United Nations. The most direct solution to the inappropriate fertilizer usage is to add only the necessary amounts of fertilizer required by plants to produce a significant yield without nutrition deficiencies. To this end this paper proposes a Smart Nutrient Disorder Identification system employing computer vision and machine learning techniques for identification purposes and a decentralized blockchain platform to streamline a bias-less procurement system. The proposed system yielded 88% accuracy in disorder identification, while also enabling secure, transparent flow of verified information.**

Keywords— CNN, RCNN, Nutrient deficiency, Machine learning, Blockchain, Image processing

I. Introduction

The mid twentieth century initiated the green revolution [1]. This resulted in a boom in agriculture, especially in the developing countries of the time [2]. The strain it would have on the environment, however, wasn't predicted yet.

John Crawford et. al. highlighted one of the reasons for topsoil depletion being the use of chemical fertilizer and unsustainable agricultural practices [3]. Soil degradation has occurred prior to the green revolution [8]. However, a rapid increase was seen with its beginning [10]. The reason for this is the introduction of fertilizers, pesticides and high yield producing varieties of seeds [11] which contributed to the overuse of soil at a faster pace [10]. Sustainable agricultural practices are mostly a combination of utilizing natural and artificial means of maintaining the soil nutrition [9]. Globally the importance of soil nutrient management has only become evident.

Currently satellite imagery and expensive Chlorophyll-meters are used for the identification of such nutrition disorders [5], which are expensive strategies to be implemented. Yet, Sri Lankan Farmers face challenges in getting a stable price for their crops and managing the crops amidst adverse climate conditions and other degrading factors such as soil degradation, pest infestations and wildlife [15]. Even though there are financial institutions provisioning credit facilities to the Agriculture sector in Sri Lanka, an extent of farmers fails to recover expenses and struggle to lead up to the next cultivation cycle [15]. In such an industrial context, expecting farmers experiencing such conditions to use the existing systems for identification of plant nutritional disorders is far from being pragmatic.

Recently agronomically-oriented technological research has been conducted on enhancing soil management practices and fertilization efficiency [14]. Currently all over the world, trends of using Blockchain, Internet of Things (IoT), artificial intelligence, robotics and automation is being integrated and discussed with relation to the agricultural field, aimed at provisioning a solution with minimum impediments [4]. A proposed approach employing accurate Machine Learning predictions utilizing an identified technique for the purpose of nutrient deficiency identification could, ideally assist in more efficient use of plant fertilizer, by suggesting accurate amounts of the best suited commercial fertilizer. This would be beneficial for the soil condition of cultivating land and could also curb costs of unnecessary investments made by farmers.

According to the FAO-ITU E-Agriculture Strategy Guide for Asia-Pacific region [13], improving the capability of farmers to access knowledge-banks, and institutions via Information and Communication Technologies (ICT) improves their productivity and profitability. Upon researching on the interactions of the farming community of Sri Lanka, in agriculture related activities, a severe problem identified was that of information asymmetry which results in middle actors capturing a margin [4] while sustainable suggestions made by the agricultural researches are being neglected. Hence, it was evident that an efficient and streamlined platform to establish communication between farmers and experts, based on the ground situation, was critical to provide the right information, at the right time, in the right format, and through the right medium.

Locally, most of the cash crops mass scale production are done in the up-country districts of Badulla, Nuwara Eliya, Kandy and Matale. Bandarawela is the second largest town in the Badulla district situated in the hill country of Sri Lanka. As in the Fig. 1, Bandarawela is considered to have much favorable conditions for the cultivation of cash crops. Field visits to and regular interactions with the 'Regional Agricultural Research and Development Centre' situated in Kahagolla, Bandarawela was a strong contribution factor in understanding the societal impact and practical context relevant to undertaking the research project.

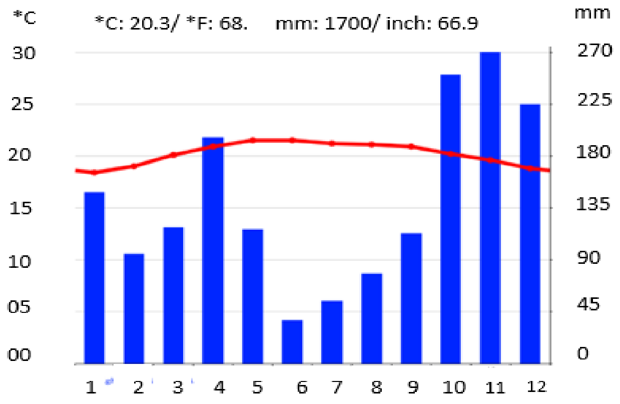


Figure 1. Bandarawela Climate Chart [22]

The eradication of poverty, hunger, acting on behalf of climate change and reducing the wastage of water are all impacted by the degradation of soil. The key objective of this project was to employ technological innovations and establish an interlink between the farming and expert communities for effective identification and ramification of nutrient deficiencies in crops, thus, maximizing on the yield in one aspect and minimizing on the degradation of soil in another.

II. Literature Review

The nutrition available in soil moves through a cycle. Moving from plants, to the organisms that devour plants until it returns to the soil through the decomposition of the bodies of the organisms that used plants as a source of food. These food sources nourish and sustain the organisms through the nutrients trapped within the plants. A lack of nutrition in soil will fail to sustain life. This is the overall impact of nutrition within soil. However, as highlighted in the introduction the soil nutrition levels are directly interlinked with farming practices around the world. A closer look at the current status on the usage of technology in this regard shows several key findings.

Firstly, an excess or deficiency in soil nutrients causes a severe loss in yield. Therefore, early and accurate diagnosis of plant nutrition disorders is a vital part of managing a farm [5]. Managing plant nutrition disorders can be divided into several activities. These are, identification of a nutrient disorder, identification of the degree of the said disorder, analyzing the soil composition to determine the reason behind such disorders and finally, to provide the most suitable remedies to the farming community. While the first three have issues directly involving field practices within farming the final activity arises out of work and interactive practices within the farming community.

The current methods used in identifying plant nutrition disorders is very expensive and highly cumbersome for field use. Currently satellite imagery and expensive Chlorophyll-meters are used for the identification of such nutrition disorders [5]. These methods require high funding which most of the farming communities cannot afford. For example, 49% of the population in Sub-Saharan Africa live on less than 1$ a day, 10 years back [6]. Sub-Saharan Africa accounted roughly of a third of the overall growth within the period of 1993 – 2005 [6] showing how heavily involved the country's labor force is in the agricultural industry. Expecting farmers from such regions to use the existing systems for identification of plant nutritional disorders is far from being pragmatic.

Meanwhile, the current methods in use to identify the degree of nutrition deficiency in plants are mainly tissue analysis and soil analysis [7]. These require laboratory expertise and is also time consuming. Thus, both methods and soil composition evaluation methods used are not practical in managing a farm by most of the farming community.

Finally, upon researching on the interactions of the farming community in agriculture related activities a severe problem identified was that of information asymmetry which results in middle actors capturing a margin [4] while sustainable suggestions made by the agricultural researches being neglected. This statement was further confirmed by the discussions held with soil experts at the Kahagolla Agri-research Institute of Bandarawela, Sri Lanka.

While the current status regarding the above four main factors are as above this research project aims in finding solutions for them using Information and Communication Technology techniques such as image processing, machine learning, block-chain and IoT. The subsequent sections will identify the research gaps existing in using such technologies, the research problems to be addressed while doing so, objectives and the methodology required to achieve such objectives.

III. Methodology

A. Identification of Nutrition Disorder in plant Leaves.

As shown in Fig. 2, any user registered as a farmer is able to upload a captured image of the leaf image through the application. Then the system predicts nutrient deficiency using the constructed CNN model. For Nutrient deficiency prediction; Nearly 1100 images were collected for the Guava, Groundnut and Citrus plants, split according to their classes. These classes are N (Nitrogen) deficiency, P (Phosphorous) deficiency, and K (Potassium) deficiency. The classified images were used for the training and validation dataset. After collecting the images, Preprocessing was done to increase accuracy and reduce the complexity of the dataset.

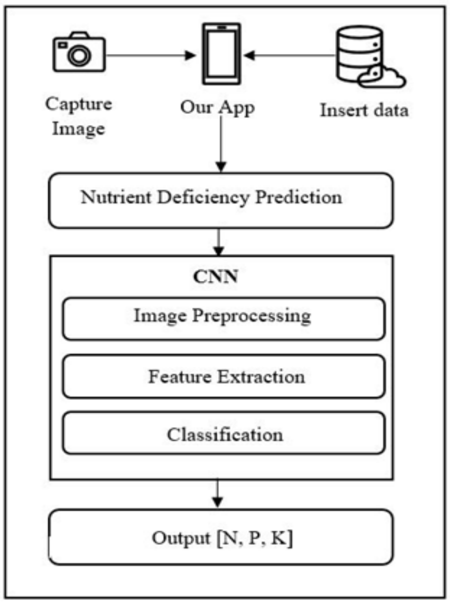


Figure 2. System Flow diagram

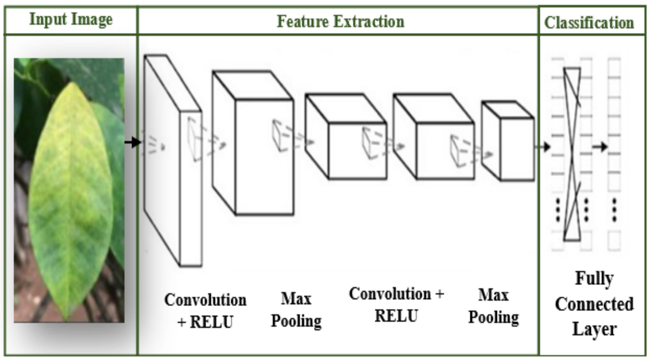


Figure 3. CNN Architecture

Table 1: Accuracy of trained model

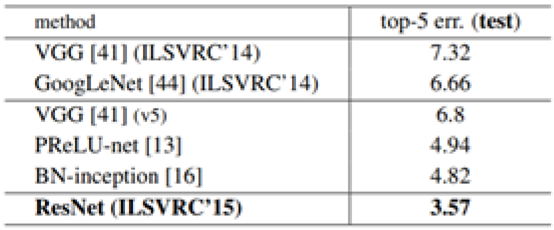
Model	Average Accuracy
EfficientnetB0	0.88
VGG16	0.43
ResNet50	0.56

Feature extraction and classification of input images will happen within the CNN model. Initially, the input image will be sent to the convolutional layer which helps to perform the extraction of features. For example, Color extraction, edge detection, and gradient orientation, etc. ReLU is used to introduce non-linearity. As demonstrates in the Fig.3, the pooling layer used to get only the needed information from the input leaf image by minimizing the parameters. Finally, a fully connected layer gets the input from previous layers such as the Convolutional layer and the Pooling layer and it flattens the input, classifies the nutrient deficiencies in leaves as output with the help of the SoftMax technique.

A pretrained VGG-16, EfficientNet-B0 and ResNet50 were used as the effective feature extractor. All these CNN architectures were pre-trained with the help of huge dataset of images. The table 1, shows the accuracy of pretrained models. Based on the average accuracy, EfficientnetB0 Architecture selected to be implemented in the plant disorder identification.

B. Identification of the degree of Nutrition Disorder in Leaves.

The degree of nutrition disorder means to simply to identify the extent of the color change in a leaf. Currently, in the field, this is done through a manual rating of the leaves by specialists. However, this method is erroneous due to inter and intra-rater variability [16]. Furthermore, such identification is carried out only by specialists which curtails information being available to the general farming population to take timely action [16]. For this purpose, the deep learning specifically used was convolutional networks with the use of a Mask-RCNN with Resnet101 and Feature Pyramid Network (FPN) backbone architecture. This was used in conducting transfer learning on the COCO weights to ensure high accuracy of the results obtained when the actual data set is used. The Restnet101 was chosen due to its high accuracy and its successful implementation against other models as shown in the Fig. 4



method	top-5 err. (test)
VGG [41] (ILSVRC'14)	7.32
GoogLeNet [44] (ILSVRC'14)	6.66
VGG [41] (v5)	6.8
PReLU-net [13]	4.94
BN-inception [16]	4.82
ResNet (ILSVRC'15)	**3.57**

Figure 4. Error rates (as a percentage) of ensembles among different methods [17]

The ResNet101 and FPN architectures mainly function in two steps. First the Mask – RCNN scans the image and proceeds with object detection after which in the second stage using bounding boxes and masks it classifies the image. The use of the FPN is to allow the features extracted in the lower and higher levels to be available at all layers [18]. The Fig.5 shows the basic structure of the entire Mask – RCNN on the basis of its functionality.

Using a Region Proposal Network (RPN) and Region of Interest (ROI) pooling in the Mask-RCNN it carries out object detection and adds a mask based on the pixels to perform instance segmentation. The mask RCNN was chosen due to its ability to perform instance segmentation as it would be more beneficial than using semantic segmentation in identifying the extent of a symptom. The Fig.6 below shows the difference between instance and semantic segmentation.

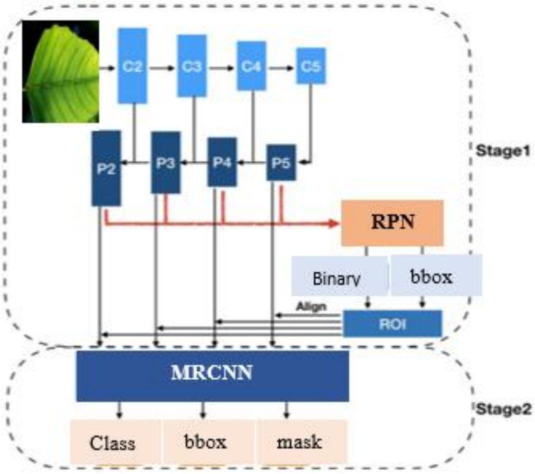


Figure 5. FPN structure based on functionality [19]

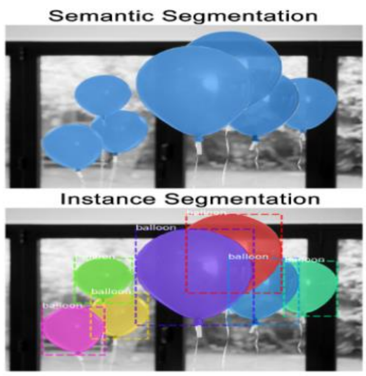


Figure 6. Comparison of instance and Semantic segmentation [18]

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times23$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Figure 7. ResNet structures with the different layers used [17]

Meanwhile, the Fig.7 shows the basic structures of the ResNet RCNN in block formation. The ResNet101 is of use in this research.

While the transfer learning was carried out, a dataset was collected. This was annotated manually to identify the healthy and unhealthy areas of the leaf. The tool used for this was the VGG Image Annotator. The collected images were divided into three categories, based on visual identification through colour changes, as showing a deficiency by 30%, between 30 – 70% and greater than 70%. These images were then sent through the Mask-RCNN post transfer learning (obtained through Matterport) with configurations as 2 images per GPU, three classes (background, healthy, and unhealthy) and a 100 steps per epoch (per training instances) and a minimum detection confidence of 0.9. The input image sizes were set at 1024 x 1024. The images that were classified with the masks were then again used and the extent of the healthy masks were calculated as a percentage of the entire leaf image. This was used to obtain the unhealthy extent of the leaf to understand the degree of the disorder.

C. *Implement a secure and distributed platform for identifying best commercial product for deficiency based on diagnosis*

A blockchain based network was identified as the ideal approach for the system to be constructed. The primary reason for this is the ability Blockchain possesses to streamline the workflow from identification of deficiency to procurement. One other reason is the sharing of data by multiple parties. The workflow can be identified as follows:

- On identification using Digital Image processing and verification via soil analysis, farmer shares relevant data (i.e., nutrient deficiency with relevant stage) with expert(s)
- On retrieval of data from farmer, expert shares Recommended Commercial Solution with instructions on quantities to be purchased from Vendor
- Farmer requests relevant products from Vendor and makes preferred choice with recommended quantity.

Information asymmetry creates an unfair bias toward the vendor. This needs to be lifted for the system to function for the benefit of the farmer. Communications between Farmer and Expert occurs in private channels which cannot be viewed by the Vendor [21].

Table 2. Logic of Employing HL-Fabric Blockchain

	Bitcoin	Ethereum	Hyperledger Fabric
Ledger	Public	Public	Permissioned/Private
Consensus	Proof of Work	Proof of Work	Solo
Smart Contract	None	Solidity	Chaincode
Mining (cryptocurrency)	Bitcoin	Ether	Optional. Not required for proposed system
Language	C++	Golang, Python	Golang, Java

Implementing a Blockchain was aimed at lifting any complexity of adding a third-party intermediary while also bringing his functionality. Overall, the feasibility of adapting a blockchain based solution for the problem is evident. Typically, blockchain employs an order-execute mechanism. Yet, the chosen Hyperledger Fabric blockchain was composed of an endorse-order-validate mechanism which resolves typical issues in Scalability, Flexibility, Performance and Confidentiality found in Blockchain. The logic behind this can be explained via the table 2

1) *Workflow*

a) *Scenario of Blockchain Component*

The Hyperledger Fabric architecture, as a private and permissioned Blockchain Network, enables privacy and integrity of data as required and also controls the level of permission each major stakeholder would have, using access control mechanisms. The workflow of this Network can be demonstrated as in Fig. 8.

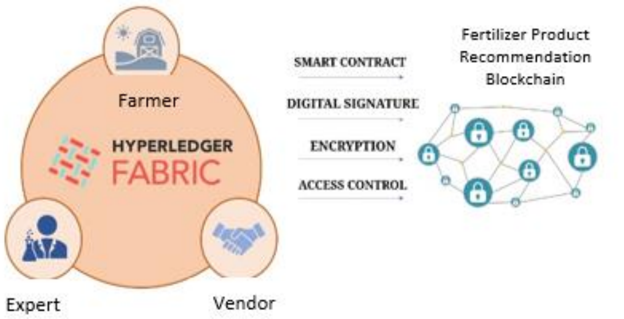


Figure 8. Scenario of Blockchain Network

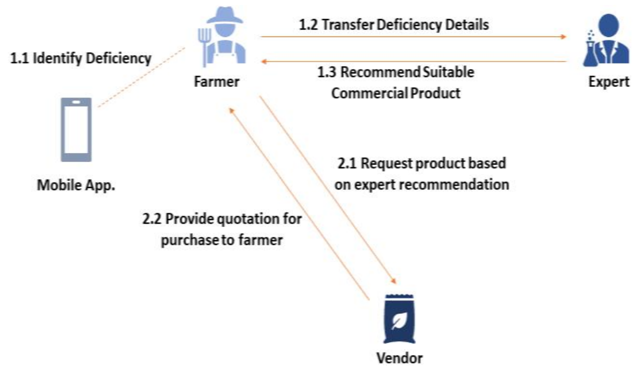


Figure 9. Structure of Blockchain Network

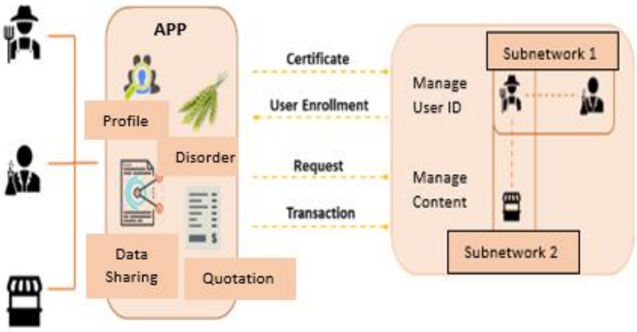


Figure 10. Diagram for Flow of System

The quotation for any products offered and any change made by vendor, can be viewed by the farmer and expert without knowledge of the vendor which is enabled by the consensus protocol. Cross-verification and lifting of information asymmetry biased to vendors can be enabled. The complete structure of the proposed system is given in Fig. 9 and Fig. 10.

b) System Definition

The system being built on a permissioned network which differentiates it from other blockchain-based systems. This feature allows only the valid participant to participate and enrol in the blockchain network through a user identity manager. User identity manager provides certificates for user enrolment and user authentication. These services are related to user identity validation, verification, and signature generation for individual users who participate in the blockchain network. The goal of the consensus algorithm is to ensure that only a single history of transactions exists, and the history does not contain invalid or contradictory transactions. The system flow would further emphasize the Fig.10

VI. RESULTS AND DISCUSSIONS

A. Results

Deep learning is applied to detect nutrient deficiency. That shows its promising results. In this research, experimentation has done with a lightweight convolutional network architecture (VGG-16, ResNet50, and EfficientNetB0) for detecting nutrient disorder and associated with its symptoms in leaves of plants.

The obtained results show reasonable overall accuracy of 88.3%, 43.8%, and 56.1% for the detection of nutrient deficiency using EfficientNetB0, VGG16 and ResNet50 backbones through dataset set of 1100 images, respectively. EfficientNetB0 achieved the best accuracy for prediction of nutrient deficiency in plants compared to ResNet50 and VGG16. Thus, it was implemented in the final version. Below Fig.11 shows the overall accuracy and confusion matrix of EfficientNetB0.

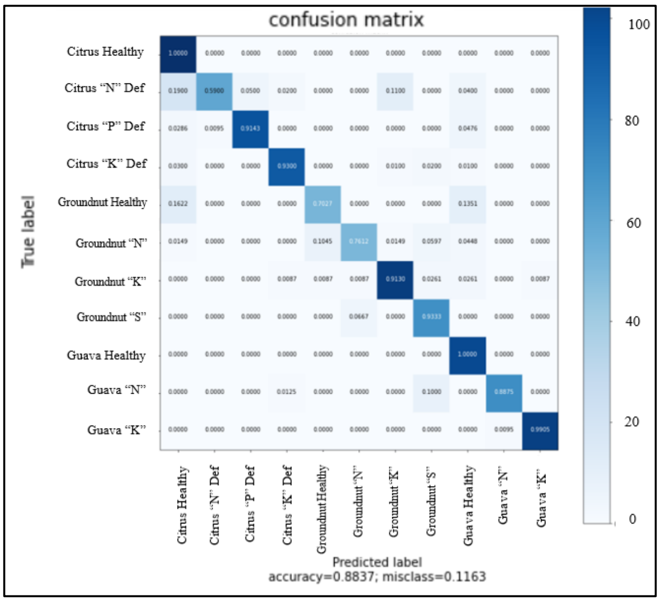


Figure 11: Confusion Matrix and Overall accuracy of EfficientNetB0

In detecting the degree of the disorder, the Mask RCNN was implemented as planned. However, a major improvement to be done in the future is the use of a controlled experiment to obtain a dataset with distinct differences in the progression of symptoms. This has been observed to give more meaningful results in identifying the extent of the disorder.

Following section will further explain test result outputs:

B. Test Outputs

1) Testing the Nutrient deficiencies in Guava, Groundnut and Citrus Plant

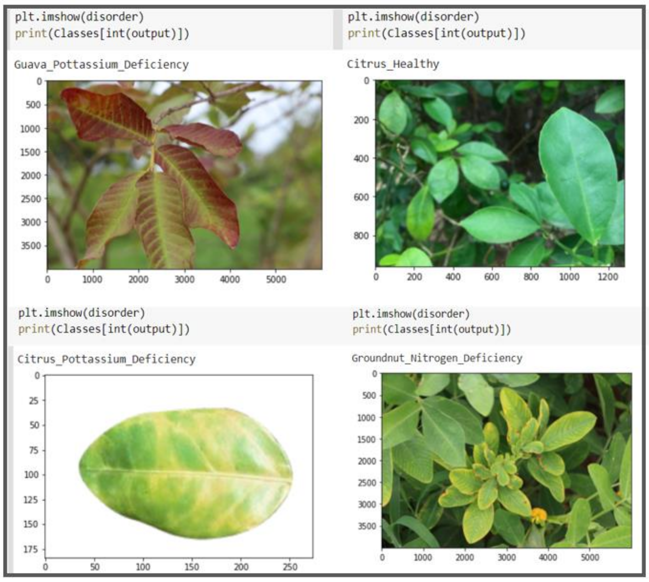


Figure 12. Sample test output images of nutrient deficiencies

C. Discussion

With the advancement of technology, agronomically-oriented technological research emerged as a contender for enhancing soil management practices and fertilization efficiency via effective interactions and communication [14]. The solution that has been structured utilizes technology to mitigate these identified issues and empower sustainable agricultural practices

Nutrient deficiency detection was implemented through the adapted CNN architecture and trained the model in the transfer learning mode of feature representation. During the research, Loss function change was experimented for the three convolutional architecture models. Each model was trained with 50 epochs. The model was trained using the collected dataset of deficient leaf with 11 classes. The VGG-16 model trained using categorical crossentrophy and reached the accuracy of 0.43. it took longest time while training the model. Further improvement is made when model was trained with ResNet50 and EfficientNetB0, EffiecientNetB0 is much faster compared to other two models. It should be noted that each epoch for the given training datasets of images took approximately 10 minutes and a learning rate of 0.001. EfficientNetB0 achieved highest accuracy of 0.88 with comparison of ResNet50 and EfficientNetB0.

According to the FAO-ITU [13], availability of right information, at the right time, in the right format, and through the right medium, influences and affects the livelihoods and profitability of farming communities. Given this context, the proposed solution utilizes a permissioned and private blockchain platform (Hyperledger Fabric) to streamline the flow of adequate and accurate information to farmers. The employed Hyperledger Fabric Network of 3 peers is an ideally effective approach with an execution time of 0.12 sec. per 10 transactions and a throughput (total committed transactions/total time taken) of 10.51 which, in both cases is evidently higher than the widely used Ethereum blockchain network [20]. While transactions occur consistently and the permissioned nature of Fabric enables higher scalability, this approach also enables a trust-free transaction ecosystem [23]. Instead of ‘who’ governs a transaction a consensus-based approach is a matter of ‘what’ is considered, successfully and effectively replicating human trust driven systems. This also introduces a distributed, automated ledger-based system which creates a trust-free setup for coordination between entities in a system. Overall, streamlining fertilizer procurement via Hyperledger Fabric would enable an auditable, decentralized and bias-free environment for fertilizer procurement.

D. Limitations

The major limitation was in the workstations used; we didn’t have access to limitless computational powers. Because of this issue, we have used a free cloud service which offers a free GPU (12Gb ram): ‘Google Colab’. It is used to train our model with speed and more efficiency.

V. Conclusion and Future Work

This project managed to build a system where commercial fertilizer recommendations could be made, based on identification of nutrient disorders. The disorders was identified using both computer vision and Machine Learning technologies and a permissioned blockchain approach was used to ensure the immutability and streamlined nature of transactions.

However, as ongoing research work, the proposed system has two signification future recommendations: first one is, develop an IoT device to measure key nutrient values of soil with the help of sensor readings and machine learning algorithms to crosscheck with the computer visionary method and next proposed future work is in collecting a better dataset for the Mask RCNN model. In machine learning, data collection and preprocessing are of critical importance. Datasets with relevance to the mechanisms and system were not readily accessible, due to the COVID-19 pandemic situation surging globally. Hence, the algorithms were trained on sample datasets obtained via controlled and progressive capture of deficiencies in a lemon, Guava and groundnut plants. Necessary proceedings were made. However, an important step in furthering this research is to carry out a controlled experiment to obtain leaves with symptoms of disorders. This can be used to provide a more distinct dataset to identify the extents of the disorders to be used in the Mask RCNN as mentioned previously.

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