SMART PLANT DISORDER IDENTIFICATION SYSTEM USING COMPUTER VISION TECHNOLOGY

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DISORDER DEGREE IDENTIFICATION

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DECLARATION

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ABSTRACT

Plant require nutrients for the survival and growth. Inadequate supply of nutrients causes nutrient deficiencies in plants that result in poor yield and the use of bad agricultural practices for its rectification. Currently there prevails a crisis of a lack of nutritive soil due to over exploitation of the topsoil available for agriculture. In stark contrast is the increasing requirement in food in the current society. In order to meet this requirement without degrading the soil further with the addition of unnecessary amounts of chemical fertilizers it is necessary to identify a plant undergoing stress due to nutritive deficiencies and treating it with only the appropriate amounts of fertilizer. This will ensure proper yield is produced while the soil isn't harmed. This research aims in identifying the stage of the nutrition disorder to recommend the necessary amount of fertilizer required. This is done with the aid of cutting-edge image processing and machine learning techniques. Early detection of nutritive disorders with the help of these techniques can provide accurate results. Investigating it's possibility is the main purpose of this research.

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1. INTRODUCTION

1.1 Overview of Agriculture as an Industry

All economic industries belong to either the primary, secondary or tertiary industry category. The primary industries constitute of industries that manufacture using raw materials from natural resources, while the secondary industries

Primary industries are where raw materials from natural resources are converted to produce goods. Secondary industries use physical goods produced from primary industries and transform them into finished products. Tertiary industries are service oriented. Agriculture falls into the primary industry category. However, the extent of the role played by agriculture is beyond that of converting raw materials into finished goods.

A historical perspective will show that agriculture is what has given rise to all the other industries. It is widely noted that human civilization begins with the rise of agriculture. Prior to this, humans are known to have been living nomadic lives, gathering animals and moving from one location to the next[1]. These nomads gathered food and engaged in hunting activities in a certain area until a lack of success made them move about again. However, at one point in history these nomads began making settlements along riverbanks and engage in agricultural activities.

According to Britannica agriculture is the activity of changing the geography of a certain area to enable the growth of selected crops and the domestication of certain animals considered beneficial to humans[1]. The associations of other activities with agriculture eventually gave rise to all other forms of industries. For example, the tools required to cultivate would give rise to blacksmiths and the industry associated, the transport required would be provided through means of logistics and even the trade and commerce that is required in carrying out transactions using the produce has all arisen due to the associations that surrounds agriculture. Therefore much of society has been shaped by the agricultural industry [2].

All other industries that have taken prominence in the 21st century have evolved in one form or the other to sustain the agriculture industry. Thus, a major deterrent to the agriculture industry would in turn negatively affect all other industries associated. It would lead one to understand that at one point in time agriculture would have been the bulk of the economy.

While currently agriculture has a significant importance in the economy, other industries are also of a significance. Agriculture can be a source of growth for the national economy, a provider of investment opportunities for the private sector, and a prime driver of agriculture-related industries and the rural nonfarm economy. Two thirds of the world’s agricultural value added is created in developing countries. In agriculture-based countries, it generates on average 29 percent of the gross domestic product (GDP) and employs 65 percent of the labor force. The industries and services linked to agriculture in value chains often account for more than 30 percent of GDP in transforming and urbanized countries.

[How did agriculture start – > the historical importance of agriculture - > which shows

What do the different regions grow, how is agriculture divided based on crops and how is poverty intwined with agriculture and in which parts is this seen. – u can highlight how agriculture in stark comparison is advanced in some parts of the world

Next show the market size and economic importance and then show the lives of the people that are contributing to this economic importance

Finally show that the reason these people are living a life with very low economic stature is because of issues related to their occupation which is discussed in the next section.]

Intro:

- The history of Agriculture to where it stands today – one para
- The demographics of today's agriculture;
    - The world – one para: outline the types of crops produced and where they are produced, how they are produced based on the different regions
    - Paras for each continent; showing the general information for each continent
    - Show how all other industries began from agriculture and how most other industries are in fact sustaining agriculture indirectly or directly
    - How cultures, societies themselves are built upon the agricultural industry and how it functions
    - The demographics of the current world and how it is linked to agriculture

1.2 Impediments faced by the Agriculture Industry and its Global Impact

The agriculture industry faces major backlash due to the spread of plant diseases on one hand. This kind of issue falls on the cultivation aspect or related work of agriculture. It is estimated by the UN that plant pests and diseases account for about 40% of the losses made to in the food industry[3]. Meanwhile another problem faced by most farmers is the lack of expertise in soil management and the lack of suitable fertilizer[3].

Another problem faced mainly by farmers is policy related[3]. The problems faced within the agriculture industry in that sense can be divided into two main categories. One related to policy making and the other related to cultivation itself.

Amongst these problems it was identified that a lack of nutrition in plants has the ability to increase the susceptibility of disease formation[4]. Thus, contributing to the 40% of loss in yield and production.

Meanwhile agriculture as highlighted in the previous section is an industry that is heavily involved in poverty-stricken areas[5]. The nature of the lives of the people in the agriculture industry also determine the methods used during cultivation. Bad soil management techniques, the lack of information transferred in the use of sustainable techniques all result due to the way the farming communities function[5].

It is estimated that, across the developing world, a total of 1.2 billion people live in poverty – as defined by the international poverty line of average daily consumption equivalent to US$1 per day per capita National data from a large number of countries suggest that the incidence of poverty in urban areas is less than in rural areas. Although the relative importance of rural poverty varies substantially from one country to another, in developing countries as a whole more than 70 percent of total poverty is found in rural areas. Similarly, hunger is also concentrated in rural areas despite the fact that they are the locus of food production.

Agriculture is a source of livelihoods for an estimated 86 percent of rural people. It provides jobs for 1.3 billion smallholders and landless workers, “farm-fi nanced social welfare” when there are urban shocks, and a foundation for viable rural communities. Of the developing world’s 5.5 billion people, 3 billion live in rural areas, nearly half of humanity. Of these rural inhabitants an estimated 2.5 billion are in households involved in agriculture, and 1.5 billion are in smallholder households.

Meanwhile, three of every four poor people in developing countries live in rural areas—2.1 billion living on less than $2 a day and 880 million on less than $1 a day—and most depend on agriculture for their livelihoods [6].

1.3 Nutrition Deficiency and Soil Nutrition Depletion’s impact of Agriculture

1.3.1 Plant Nutrition Deficiencies and Identification

Plant nutrients can be categorized. These essential elements are classified as either macronutrients (N, P, K, Ca, Mg, S) or micronutrients (Fe, Mn, Cl, B, Cu, Zn, Ni, Mo) based on the concentration normally present in plants. Each is essential for particular functions in the plant. Plant nutrients are also important in disease resistance and fruit quality, and the balance between the various elements can affect plant health and productivity. In addition to the essential nutrients, several elements (Cl, B, Na) may be toxic to the tree if present at excessive levels in the soil or irrigation water [7].

Soil analysis typically provides information on available nutrient levels as well as soil conditions such as pH, cation exchange capacity (CEC, the ability of a soil to retain cations for subsequent release into the soil solution), and salinity that may be important in determining the cause of a deficiency[7].

Leaf analysis is more useful in diagnosing mineral deficiencies and toxicities in tree crops than soil analysis. The mineral composition of a leaf is dependent on many factors, such as its stage of development, climatic conditions, availability of mineral elements in the soil, root distribution and activity, irrigation, etc. Leaf samples integrate all these factors, and provide an estimate of which elements are being adequately absorbed by the roots [7].

When a nutrient element insufficiency (deficiency and/or toxicity) occurs, visual symptoms may or may not appear, although normal plant development will be slowed. When visual symptoms do occur, such symptoms can frequently be used to identify the source of the insufficiency[8].

Visual symptoms of deficiency may take various forms, such as stunted or reduced growth of the entire plant with the plant itself either remaining green or lacking an over-all green colour with either the older or younger leaves being light green to yellow in colour Some common visual symptoms are as follows. For the purpose of study, the disorders related to N, P and K have been identified as these are of major significance owing to the fertilizer use mainly contributed by N, P and K[8].

Nitrogen (N) Deficiency shows Light green leaf and plant colour with the older leaves turning yellow, leaves that will eventually turn brown and die. Plant growth is slow, plants will be stunted, and will mature early. Excess in N will show plants in dark green in colour and new growth will be succulent; susceptible, if subjected to disease and insect infestation; and subjected to drought stress, plants will easily lodge. Blossom abortion and lack of fruit set will occur.

Phosphorus (P) Deficiency Plant growth will be slow and stunted, and the older leaves will have a purple coloration, particularly on the underside[8]. Excess Phosphorus excess will not have a direct effect on the plant, but may show visual deficiencies of Zn, Fe and Mn. High P may also interfere with the normal Ca nutrition, with typical Ca deficiency symptoms occurring.

Potassium (K) Deficiency On the older leaves, the edges will look burned, a symptom known as scorch[8]. Plants will easily lodge and be sensitive to disease infestation. Fruit and seed production will be impaired and of poor quality. Excess Plants will exhibit typical Mg, and possibly Ca deficiency symptoms due to a cation imbalance.

Nutrients can affect disease resistance or tolerance. Disease resistance of the host is its ability to limit the penetration, development and reproduction of the invading pathogens[4]. On the other hand, tolerance of the host is measured in terms of its ability to maintain its own growth or yield in spite of the infection. Resistance depends on the genotype of the two organisms, plant age and changes in the environment. Although plant disease resistance and tolerance are genetically controlled, they are affected by the environment and especially by nutrient deficiencies and toxicities[4].

One of the first observations of the effect of nutrients on disease development was that fertilization reduced disease severity when plants were under deficiency, as fertilization optimized plant growth. When N was applied to cereal crops, take-all (Gaeumannomyces graminis) was reduced. Also, P reduced both take-all and pythium root rot infection in cereal crops [4].

Nitrogen is the most important nutrient for plant growth and there is an extensive literature about the effect of N on diseases, because its role in disease resistance is quite easily demonstrated[4].

Phosphorus is the second most commonly applied nutrient in most crops and is part of many organic molecules of the cell (deoxyribonucleic acid (DNA), ribonucleic acid (RNA), adenosine triphosphate (ATP) and phospholipids) and is also involved in many metabolic processes in the plant and also in the pathogen. However, its role in resistance is variable and seemingly inconsistent. P has been shown to be most beneficial when it is applied to control seedlings and fungal diseases where vigorous root development permits plants to escape disease. Phosphate fertilization of wheat can have a significant effect and almost eliminate economic losses from pythium root rot [4].

Potassium decreases the susceptibility of host plants up to the optimal level for growth: beyond this point, there is no further increase in resistance which can be achieved by increasing the supply of K and its contents in plants. The high susceptibility of the K-deficient plant to parasitic disease is due to the metabolic functions of K in plant physiology. Also, K may promote the development of thicker outer walls in epidermal cells, thus preventing disease attack[4].

1.3.2 Soil Nutrition and its Interaction with Plants

Soil security is a new concept that has arisen during a time of emerging international response to the increasingly urgent problems that face the global soil stock. Soil security refers to the maintenance and improvement of the world’s soil resources so that they can continue to provide food, fiber and fresh water, make major contributions to energy and climate sustainability, and help maintain biodiversity and the overall protection of ecosystem goods and services. History stands as a warning to our modern societies. Whole civilizations have fallen and collapsed when their stock of fertile soils washed or blew away[9].

The world now faces a modern soil crisis that eclipses those of the past. Soil degradation is a global phenomenon with many faces [9].

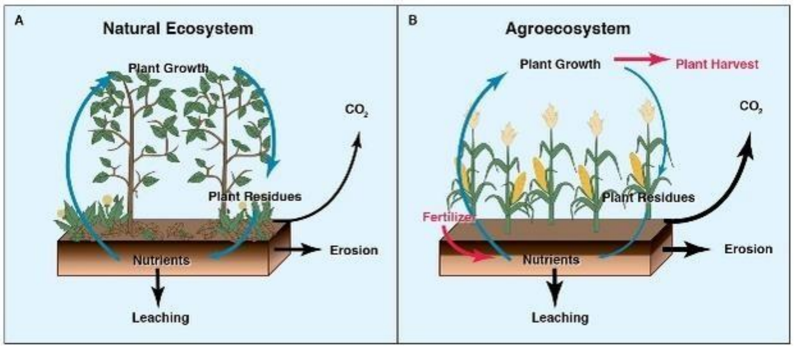

Figure 1.1 Nutrient Cycle in natural eco-systems and agro-ecosystems

Source: Adapted from [10]

Soil is similar in nature to a living organism and a has a very dynamic nature to it. Naturally it cycles the many nutrients present within through many interactions by the multitude of microbes present in it. Figure 1.1 shows the natural cyclical nature of nutrients. It also shows the constant removal of nutrients from the soil in agriculture through harvesting, which, results in breaking the cycle of nutrients returning to the soil. Furthermore, it shows more likelihood in nitrate leaching, soil degradation and soil erosion in agricultural practices. Thus, maintaining necessary quantities of soil nutrients required for plants is a constant requirement to obtain the good yields in an environmentally friendly manner [10].

1.3.3 Effect of Soil Nutrition Depletion to Farming

An estimated 55 per cent of the world's desertified land is attributable to soil degradation. Land degradation is estimated to affect 23.5 per cent of global land area and has resulted in 1–2.3 million hectares of agricultural land becoming unsuitable for cultivation. Much of this degraded area faces increasing pressure from development as a result of increasing population. Around 1.3 billion people in developing economies live in marginal areas and on ecologically fragile lands that are prone to severe land degradation [9].

1.3.4 Global Impact on Economy and Food Security Due to Nutrition Deficiencies

1.4 Impact of Farming Methodologies and Techniques on Agriculture

1.4.1 Evolution of Farming Methodologies

1.4.2 Inadequacies of Sharing Knowledge within the Agriculture Industry

1.4.3

1.5 Agricultural Policies and its Impact on the Industry

1.5.1 Agricultural Policies within Sri Lanka and its Impact on the Industry

1.5.2 Impact of Fertilizer and Vendor Distribution System on Farmers in Sri Lanka

1.5.3 K

1.6 Overview of Providing Cross-Domain Smart Solutions through Technology

1.6.1 Evolution of Technology and Factors Influencing Smart Solutions

1.6.2 Technology Usage in Agriculture

1.6.3 Technological Overview of Proposed Solution in Identifying Nutrition Deficiencies

1.6.4 Overview of Technologies Used in Symptomatic Degree Identification

1.6.5 Mask RCNN and Convolutional Neural Networks

1.6.6 COSFIRE and Convolutional Neural Networks

1.7 Nutrition Deficiency Degree Identification in Plants Using Mask RCNN and COSFIRE (Write in a way that the COSFIRE section can be removed)

1.8 Literature Review of Identifying Degree of Nutrition Disorder using Computer Vision Techniques

The degree of a nutrition disorder requires in identifying the severity of the disorder at a certain stage. In plants the amount of nutrition required varies amongst different growth stages [7]. In order to identify the degree of a nutrition deficiency, currently soil analysis or leaf analysis is carried out [7] in the field. Both soil analysis and leaf analysis require expert training to conduct and laboratory facilities[7]. Furthermore, they are both time consuming and cannot be practically applied in the field by most independent farmers. In this case, farmers usually add fertilizers based on the instructions provided during field trials etc [11].

According to the soil researchers at the Kahagolla Agri Institute of Bandarawela, Sri Lanka this process is usually continued without assessing the nutrient content in the plants or the soil unless a special requirement arises. The general practice of applying fertilizer is done in this manner. Apart from this the nutrient deficiency degree has been identified in several works of research carried out with the use of image processing and machine learning. However, it must be noted the amount of research carried out on plant nutrition disorder identification using image processing and machine learning is relatively low.

The research works identified have usually been done to identify a nutrition deficiency from a set of deficiencies within one plant. Thus, the overall research work done to analyse the severity of a nutrition deficiency is substantially lower. However, from the literature reviewed thus far, the identification of nutrition deficiency at different growth stages for maize, rice and tomato plants will be discussed in this section. The research paper on 'Identifying the nutrient disorder based on the temporal dynamics of the leaf morphology and colour' [12] discusses the usage of morphological and colour features to distinguish the leaf growth status.

The Relative Growth Rate (RGR) has been used to assess the dynamic morphological or colour changes in the plants with respect to the deficiencies. The data sets were then collected during an interval of every 3 days each and 6 days each. Meanwhile, the images were collected in a closed setting to reduce the external effects and a desk scanner was used for this purpose. Finally, the collected data samples were then processed with the use of MATLAB 2013b [13]. For identification of the nutrition disorders in the same research paper discriminant analysis has been used for machine learning. Thus, this paper has used an unsupervised model in identifying the degree of the nutrition disorders for N, P and K. The experiment carried out was done by collecting specific data sets for two phases of growth in area, length and colour 4 observed in rice leaves. The accuracy levels observed for identification of the deficiency symptoms for each phase was 73.7% and 71.4%.

While the previous paper studied the two specific growth phases 'Use of artificial vision techniques for diagnostic of Nitrogen nutritional status in Maize plants'[14]studied the accuracy in obtaining results for identification of Nitrogen deficiency stage based on the location of the plant leaf. The results showed marked differences based on location with an accuracy of 98% in the mid area of the leaf showing the highest in being identified. Meanwhile, the method used was a combination of techniques referred to as artificial vision system using Gabor wavelets techniques in feature extraction, fractal dimension used with machine learning. Even-though the research didn't provide enough insight into the processes of machine learning a wide variety of feature extraction methods were employed in the system. However, the important factor to note between the two works above are the different parameters in leaves that could be used in investigating nutrient deficiencies. A data set that could be used to train the model to identify the relevant disorders accurately in other plants, subsequent to training would be helpful. While the former used area of the leaf to measure the deficiency symptoms the latter used the changes in features in different parts of the leaf.

The research on identifying macronutrient deficiencies on the development of tomato plant using Convoluted Neural Network (CNN) in forecasting and classifying [15] has used Inception-ResNet v2 architecture with autoencoder and ensemble averaging as a means of validation. While ensemble averaging is a technique used to improve the performance of machine learning [14], the autoencoder is used to train the neural network [15]. All plants were grown in a green house environment and the accuracy of rates were 87.273%, 79.091% and 91% for the Inception-ResNet v2 model, the autoencoder and ensemble averaging respectively. The Inception-ResNet v2 model proposed is of supervised nature while the autoencoder uses unsupervised machine learning in the classification of the disorders. While both models were based on CNN using several feature maps, the ensemble averaging technique has been used to combine the two models and bring about an increase in predictive accuracy. The images collected for the dataset was through a mobile phone and a digital camera [15]. Even though the research was carried out to show the nutrition disorders at the various stages in the tomato plant, the paper didn’t elaborate as mentioned in the first two about the stages.

However, these three papers allow a comparison in the models used, the accuracy achieved in identifying disorder degrees for the relevant models and the methods used in obtaining a data set. This comparison helps to identify the research gaps that can be covered in this research component as opposed to what has already been covered.

1.9 Research Gap and Scope of Research

1.10 Research Problems and Research Questions

1.11 Research Objectives

Testing an introduction here

Table 1. 1 Test Table

2. METHODOLOGY

2.1 Overview of Current Field Mechanisms in Identifying Nutrition Disorder Degrees in Plants

What is currently done in the field

2.2 Contribution of Computer Vision in Identifying Nutritional Disorder Degrees in Plants

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 [15]. Furthermore, such identification is carried out only by specialists which curtails information being available to the general farming population to take timely action [15]. 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 image below.

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 2.1 Error rates (as a percentage) of ensembles among different methods

Source: Adapted from [16]

Figure 2.2 Feature Pyramid Network Architecture

Source: Adapted from

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]. Using a Region Proposal Network (RPN) and Region of Interest (ROI) pooling in the Mask-RCNN it carries out semantic segmentation by masking and instance segmentation. The above images show the difference between instance and semantic segmentation. Meanwhile, the above image shows the basic structures of the ResNet RCNN in block formation. The ResNet101 is of use in this research.

- The kind of model chosen and why?
- How we chose supervised learning and why
- How we chose the languages we chose the opencv part; how we decided on it
- Can add a gantt chart to show the propsed plan and explain how it changed during the course etc
- Add details on implementation how the servers were made ready, the lack of computation power in your local pc to run the relevant models etc -→ explain those sections well too

2.3 Data Collection and Dataset Creation for Machine Learning Application

A dataset of 300 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 300 images collected were divided into three categories with 100 images each for images 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, five classes (background, leaf, 30% deficiency, 30 – 70% deficiency, greater than 70%) 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 to calculate the percentage of deficiency using OpenCV to provide a numeric value as an output to the user.

2.4 Implementation of the Mask RCNN and its Usage

2.5 Implementation of the COSFIRE and its Usage

2.6 Integration to Main System

3. TESTING OF IMPLEMENTATION AND RESULTS

3.1 Overview of Testing phases and Implementation

3.1.1 Using Dataset with Leaves Containing Different Colour Variations

3.1.2 Using Dataset with Rater Recommendation

3.2 Results of Testing and Implementation Phases

3.2.1 Using Dataset with Leaves Containing Different Colour Variations

3.2.2 Using Dataset with Rater Recommendation

3.3 Research Findings

3.4 Discussion and Future Work

4. CONCLUSION

Figure 4.1

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6. APPENDICES