

# Technology for Kisan Samanvayam: Nutrition Intelligibility of Groundnut Plant using IoT-ML Framework

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**Abstract**— Neolithic Demographic transition resulting the reduction of habitable land for cultivation. Hence the smart agriculture is the only way to cater higher food demand. The farming community of developing countries like India needs Kisan Samanvayam with futuristic technologies for financially viable cultivation. Technology place vital role in economically nourishment of soil fertility and crop management. In this regard we proposed IoT-ML framework for remotely assessing the soil nutrients (N, P,K), PH and early stage detection of crop deceases. Android APP which is a part and parcel of the frame work enable the farmer to have real time visual statistics of the soil nutrients, notifications and suggestions regarding to the crop management. JXCT Soil NPK sensors, PH sensors, Dual Core ESP32 Controllers, Firebase Cloud and Random Forest Decision Tree machine Learning Algorithm, Micromlgen serve this purpose. Unlike Solitary sensor for entire field, we have divided a hector into four subregions for effective monitoring local region needs. The presence of IoT with TinyML increased the robustness of the framework and results are encouraging with sandy loam soil.

**Keywords**- Smart farming, Internet of Things, Machine Learning, ESP32, NPK sensor, PH sensor

## I. INTRODUCTION

During COVID-19, Agriculture is the only industry that protected from declining GDP of OUR Country. Horticulture contributes around 30.4 percent of our GDP growth with state of art technological support [1]. However, the technological benefits not fully explored in agriculture domain. Farmers are compelled to adapt mechanized tools for their support as the available manpower support is getting reduced year by year [2]. Conventional Machine learning models are based on sophisticated higher cost Hardware, consume more power and are not suitable for real time responses. Further they are not financially viable to the farmer and also not compatible with mobile devices. As an alternative, Researchers have proposed Internet of Things (IoT) with Edge computing for smart agriculture. IoT with machine learning through edge devices with sensors are capable of giving valuable inputs to the farming community about soil moisture, Fertility of soil, humidity level, temperature level, nutrient status of the plants, growth of the plants and remote water management. These inputs are handy

while analyzing and dealing with suspected plant deceases. With early stage detected symptoms and proper remedial approaches, we can minimize the crop loss there by increasing the yield and financial status of the farmer.

In order to increase the yield farmers knowingly or unknowingly using of excessive fertilizers. Environmental pollution, increasing the soil acidity and disturbing soil eco system are the side effects of excessive fertilization. Good nutrition is essential for optimal crop yield. Plants require several chemical elements like N, P, K, Ca, Mg, S, Fe, Mn, Zn, Cu, Cl, B and Mo to support their life cycle. All these Nutrients are divided into two groups mainly macro nutrients and micro nutrients [3]. Plants require Macro nutrients like Nitrogen, Phosphorous, and Potassium in higher concentrations in their entire life cycle whereas Micro nutrients such as iron can be required in tracer quantities. Because of this reason Macro Nutrients are applied directly to the soil and Micro nutrients can be applied either to the soil or to leaves. Plant growth and health depends on the amount of available nutrient present in soil which

is shown in Figure1 and it divides into 3 ranges such as deficiency range, sufficiency range and Toxicity range. Growth can be affected if the amount of available nutrient levels of a plant are not in the sufficient range [4]. When nutrients are not presented in adequate amount it results in nutrient deficiency. Whereas nutrients are presented in excess than it needs it results in toxicity range. Deficiency is more frequent than nutrient toxicity. Deficiency of different nutrients and its effect on the plant growth is shown in Figure 1.

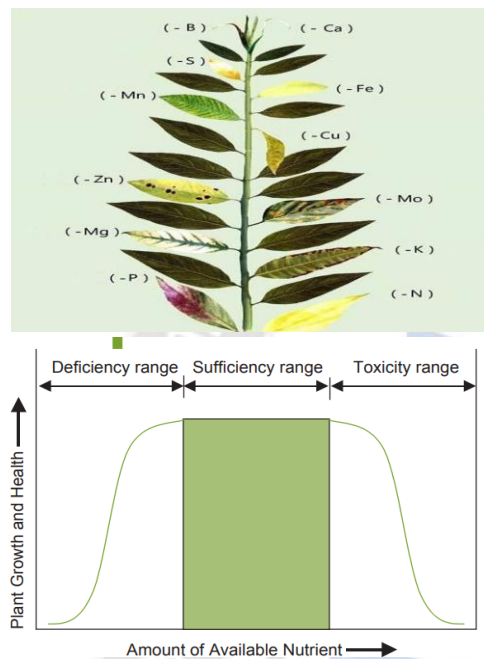


Figure 1. Soil Nutrient and ranges

Nitrogen (N) encourages plants to mature normally and produce large amounts of thick, green leaves and this facilitates photosynthetic activity. Low nitrogen levels inhibit plant growth and result in the loss of their green tinge, resulting in yellow-green leaves (called chlorosis), also it yields to fewer and weaker quantities of fruit & vegetables and these symptoms will spread throughout the plant. In contrast higher nitrogen levels allow the plants to concentrate more on leaves and less on flowering and production. It is shown in Figure 2 (a) [5]. One more important micro nutrient for plant growth is Phosphorous (P). The proper amount of it encourages plants for strong growth of the roots, blooming, healthy fruits and seeds shown in Figure 2(b) [6]. One more important Potassium (K) encourages root and general plant growth. In addition to that it also fortifies cell walls, supports stem strength enhancement, provides resistance from wind, weather changes and weight. Its deficiency slows down CO<sub>2</sub> absorption by which its rate of photosynthetic process and reduces the metabolism of a plant shown in Figure 2(c) [7].

Nutrient deficiency and toxicities are determined by using quantitative approaches such as soil testing, analysis of

Plant growth and qualitative approach such as visual observations. This research paper focused on determining the deficiencies of macro nutrients by using NPK sensor and Machine Learning algorithms.

Chinnadurai Chinnaraja et al [8] identified major diseases associated with tomato crop, some of them are early blight, Septoria leaf spot, southern blight, Rhizopus rot, bacterial spot, bacterial speck, powdery mildew, grey mould and bacterial wilt. The nutrient adequacy of the soil, high humidity and intermittent shower associated with weather are the main reasons for Septoria leaf spot disease of tomato crop.

The symptoms of "Alternaria", fungus prone disease with genetically modified BT cotton seeds, in cotton crop were identified in early stages using morphological operations on



(a) Nitrogen (N) Deficiency

(b) Phosphorus Deficiency



(c) Potassium Deficiency

Figure 2. Deficiency of Nutrients

cotton leaf images [9]. They have used Zymo Research Quick DNA kit for extraction of Genomic DNA of fungal cultures along with pathogenicity test. The fungus culture impact is common even in potato and tomato crops.

G. Thiribhuvanamala [10] et al., exhaustively worked on the diseases, favorable conditions and remedies of mango fruits. They identified high temperature (25-31 degrees) is most favorable for spreading Stem end rot disease and also low temperature (13- 15 °C) with humidity (64-72%) is most favorable for spreading Powdery mildew disease. The treatment they suggested is the spray of water along with proportional fertilizers at regular intervals.

Issues associated with crop health monitoring [11], Disease detection and classification [12] explored machine

learning and deep learning techniques. IoT frame works are developed to show their feasibility to perform real time predictions in agriculture domain by using automate data collection, data storage and analysis [13,14,15] .

Balaji et al. [16] focused on Fuzzy logic system for improving crop farming through careful planning by Agro-technicians. The objective is to attain higher yields while minimizing the utilization of resources and agricultural land. Jawad et al [17] have confirmed the effectiveness of cloud computing devices in farming and discussed how devices handles all the operations such as gathering the data from sensors, images from the field computing process getting the data form GPS coordinates etc., Sakthipriya et al[18] emphasizes the usage of Technologically sophisticated control with the help of sensors, controllers and actuators. GPS and a smart robot capable of performing farm tasks such as sowing, crop-dusting, weeding, moisture level measuring and remote monitoring. Rehman et al. in [19] introduced a framework aiming water conservation and reducing the wastage. Mallikarjuna et al [20] proposed deep learning with VGG 19 architecture for dealing with side effects of COVID-19. However, their model is cannot be fitted into IoT-edge devices due to its resource volume.

## II. EXISTING APPROACH

Macro nutrients such as Nitrogen, Potassium, Prosperous are main responsible for healthy and diseases free plants/leaves. One hector land needs to provide 112 kg N, 27 kg P2O5 and 34 kg K2O for healthy groundnut crop. Nitrogen is responsible for good leaf growth and color along with healthy growth of the plant. The strength of the root and groundnut bunch of a plant required sufficient phosphorous. Potassium is responsible for photosynthesis process, supply of proper nutrients and water to the plants there by providing the disease resistance. The Potential of Hydrogen(pH) of the soil represent the status of nutrients. It was found that the PH value of the soil between 4-5 is not all suitable as it results deficiency of all nutrients. While the PH value 6-7 is idle for the growth of ground nut crop.

The traditional approach associates with farmer carrying the soil sample to the recognized soil test center and wait for the findings. The test center in turn takes a batch of samples and subject them to various electro chemical / Spectro analysis / soil conduction tests. These tests consume one week in a rapid process. BY the time these results reached to the farmer enough damage might have occurred to the plant or it may be too late to take any preventive action. Some researchers tried machine learning models which consider entire soil region as a single unit and perform the treatment with global information of entire area. Our proposed approach is capable of localized treatment with local information of each sub region. This will avoid excessive/ Un necessary usage of fertilizers for crop management. This

Research paper focused on determining the Localized deficiencies of Macro nutrients by using NPK sensor and Machine Learning algorithms. Further technology is deployed so that the farmer himself know the soil status nutrients with the help of sensors on a real time basis with the Mobile APP and remedies can be suggested to overcome crop growth related problems if any. Thus, the technology is empowered for rural India in general and farming community in particular. Our Kisan Samanvayam frame work is in tune with the mission of Atma Nirbar Bharath.

## III. ARCHITECTURAL COMPONENTS AND METHODOLOGY

### A. JXCT Soil NPK Sensor

It detects the amount of nitrogen, phosphorus, and potassium in the soil and assesses soil fertility by measuring the conductivity transformation produced by nitrogen, phosphorous, and potassium absorptions in the soil. It is extensively utilized in soil research, greenhouse agriculture, rice cultivation, and vegetable production. Spectrometers or optical sensors have been used to determine the soil nutrients in earlier approaches. However, the spectrometers limits the accuracy 60 to 70 percent and in many cases they are not practical. In this regard we have used JXCT Soil NPK sensor to overcome the above problems. It provides the high accuracy data, portable, ability to respond quickly at minimal price. NPK sensor is connected to any micro controller along with Modbus RS485. JXCT soil NPK sensor is appropriate for all categories of soils because of its premium quality probe. The probe is resistant to rust, electrolysis, salt, and alkali degradation. The sensor uses relatively little power and runs on 9 to 24 volts.



Figure 3. JXCT NPK Sensor and Wiring Instructions

1. Modbus Commands for NPK Sensor

These commands are used to instruct the Modbus device to modify the register contents and to read data from I/O port. These commands hold the address of the required device in the range of 1 to 247.

It is also referred as inquiry frame. This frame can be sent to all the devices which are connected to the Modbus, but only the corresponding address device can be responded and act immediately. The Nitrogen (N), Phosphorous (P), and Potassium (K) values can be read using one of three distinct inquiry frames provided by the NPK Sensor (K). Instruction manual contains the formats of all three inquiry frames.

a) General format for the inquiry frame is:

{Hex-address code (AC), Function code (FC), Starting Register address (SRA), length of register(LR), Lower byte of CRC (CRC\_LB), Higher byte of CRC(CRC\_HB) } as illustrated in Table1.

b) General format for the response frame is:

{ Hex-address code (AC ), Function code(FC), Effective number of bytes(EB), N/ P/ K value, Lower byte of CRC (CRC\_LB), Higher byte of CRC(CRC\_HB)} as illustrated in Table2

TABLE I. FRAME FORMAT INQUIRY FRAME

	AC (in Hex)	FC (in Hex)	SRA (in Hex)	LR (in Hex)	CRC_ LB (in Hex)	CRC_ HB (in Hex)
Nitrogen	01	03	00 1E	0001	E4	0C
Phosphorous	01	03	00 1F	0001	B5	CC
Potassium	01	03	00 20	00 01	85	C0

TABLE II. FRAME FORMAT RESPONSE FRAME

	AC (in Hex)	FC (in Hex)	EB (in Hex)	Value (in Hex)	CRC_ LB(in Hex)	CRC_ HB(in Hex)
Nitrogen	01	03	02	00 20	B9	9C
Phosphorous	01	03	02	00 25	79	9F
Potassium	01	03	02	00 30	B8	50

Tuning

The hexa decimal response value obtained from sensors are converted into equivalent mg/Kg. For Example , If we get hexa decimal value of Nitrogen is 0X20H, it's decimal equivalent value is 32, which specifies that the content of nitrogen in the soil is 32mg/kg.

B. PH Sensor

Soil pH is a crucial aspect for the growth and well-being of plants. An imbalanced soil pH, either too acidic or too alkaline, can limit the access to necessary nutrients and hinder plant growth. A soil pH sensor is a device that determines the acidity or basicity of soil by measuring the soil's hydrogen ion concentration. This sensor typically includes a probe that is inserted into the soil to assess its electrical conductivity. The collected data is then transmitted to a computer or monitoring device where it undergoes analysis and the soil pH is computed. The use of a soil pH sensor enables farmers and gardeners to monitor soil pH levels and make adjustments to maintain optimal soil conditions for plant growth.

C. ESP32

ESP32 is a 32-bit microcontroller chip manufactured by Espressif Systems which is shown in figure 4. Embedded devices can communicate with it by using built in wireless Bluetooth and Wi-Fi connectivity. ESP32 can be used in various IoT functions such as networking, data processing, Peer to Peer connectivity and webserver developments. It can be functioned by using a maximum clock frequency of 240MHz. A capacitive touch screen, an ADC, DAC, a UART, an SPI, and an I2C interface are the built in components of the ESP32.

D. Random Forest Algorithm

It is a popular and frequently employed supervised machine learning method for classification and regression problems which is made up of with several decision trees [21,22]. It produces the final output based on the majority of votes of predictions in case of classification and takes the average in case of Regression. This algorithm results high accuracy even without hyperparameter tuning. It is mainly work on with ensemble technique such as bagging that combines many weak.

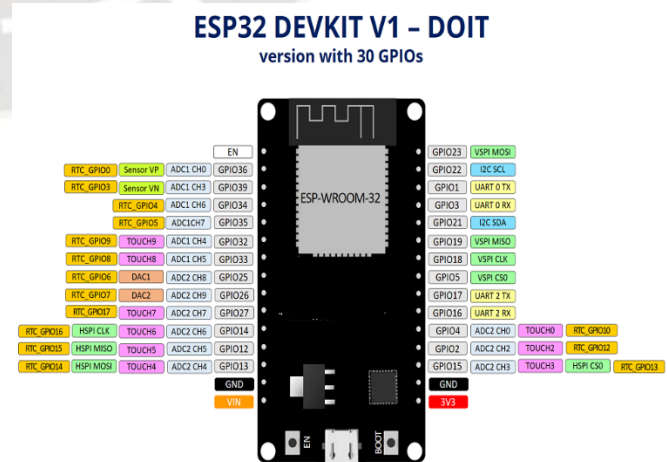


Figure 4. GPIO configuration of ESP32

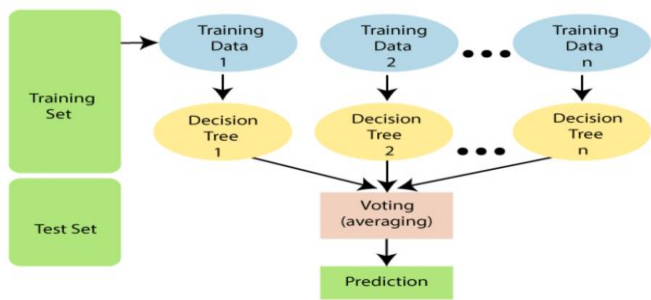


Figure 5. Random Forest Algorithm Structure

classifiers to provide solutions to complex problems. Some of the important characteristics of this algorithm include providing greater accuracy than decision trees, effectively dealing with missing data, and confronting the issue of overfitting. Classifier accuracy is proportional to the number of decision trees of the forest.

As shown in the above figure 5, Random Forest algorithm is applied on training data after the data alienated into training and testing sets. Row sampling and feature sampling is performed to create subsets of training data set.

In the context of decision tree model training, a random subset of Y features is selected from a training dataset comprising X observations. The chosen feature that produces the most effective split is then employed to iteratively split nodes. Individual decision trees are formed for each subset and outputs are collected from each tree. Prediction is given based on the majority of voting or aggregation of predictions from all the trees.

$$\text{Random Forest} = \text{Decision Tree} + A + B + C \quad (1)$$

where

A = Bagging (Row Sampling with Replacement)

B = feature bagging(column sampling)

C = aggregation(mean/median, majority vote)

Gini index, which verifies the purity and impurity of the data split, can be used to select a feature or split the data. A pure split refers to the acquisition of “Yes” or “No” values. The feature with the lowest Gini index or impurity will be opted as the root node. Gini index, mathematically calculated as,

$$GI = 1 - \sum_{x=1}^n (p_x)^2 \quad (2)$$

$$= 1 - [(P \text{ pos})^2 + (P \text{ neg})^2] \quad (3)$$

Where Probability of positive class and negative class are denoted by Ppos and Pneg.

Weighted Gini index which is total Gini index of this split is calculated as,

$$\text{Weighted Gini Index} = \sum_{x=0}^n \frac{nx}{n} GI(x) \quad (4)$$

In similar way, Gini index of all possible splits is calculated and the feature with the lowest Gini index represents low level of impurity is selected as root node.

#### E. App development Framework

Kodular is a popular online platform for coding-free mobile app development. Its block-based editor and drag-and-drop components make app creation easy, even for users without coding knowledge. Kodular offers features like project management, GUI, work flow management, and a designer-friendly interface. It supports a large number of Android devices, such as LG, Samsung, HTC, and Microsoft Surface, and has various connectivity and database components suitable for IoT app implementation. Clock event block along with google firebase component are used to interact with Bi-directional communication user and cloud database.

#### F. Google Firebase database

It offers real time data management in the cloud in terms of tag and value due to its NO SQL data handling ability. It provides security and global accessibility for the user project. The premium version support advance data analytics on remotely sensed information. First user has to create a project with necessary tags and generates secret database key for the project. The project can be deployed in Test mode so that cost free usage of Google Cloud.

#### G. Micro ML tool

Micro ML is a tool for making machine learning techniques accessible to microcontrollers. It converts machine learning algorithms into optimized C code, which can then be deployed on microcontrollers such as ESP8266, ESP32, Arduino UNO, and Arduino Nano. This tool can port various classifiers, including Decision Tree, Random Forest, SEFR, and PCA, to C language and run them in the Arduino IDE.

#### H. Methodology

The proposed framework shown in Figure 6 illustrates architectural aspects of the framework. It associates the model building, testing and App management. The solution is proposed in three phases.

Phase1: Pre plantation of soil health

Phase2: Periodic nutrition status of the plants

Phase3: Early detection of plant deceases using Leaf analysis

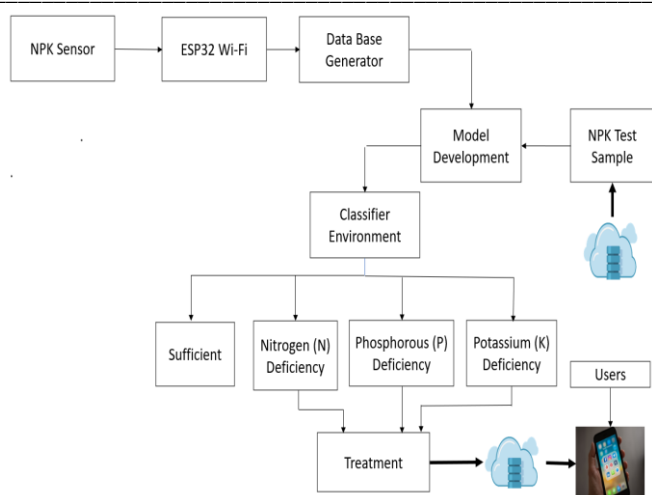


Figure 6. Framework of proposed approach

Three Machine Learning Models are devised for the phases which will work independently. The concerned dataset is developed locally with the published inputs taken from Tamil Nādu University. Random forest algorithm has been adopted while developing our machine learning models.

1. Phase1 Procedure

**Step1:** NPK machine learning model is developed and deployed in the server ESP32 controller. Locally generated dataset containing 4000 samples which contains sufficient nutrients, Nitrogen deficiency(N), Phosphorous deficiency(P) and Potassium deficiency(K) is used for model generation. Table3 provides desired Nutrient values for NPK at different stages of groundnut Crop. Table 4 provide threshold values for the respective nutrients.

TABLE III. STAGE WISE NPK VALUES FOR A SAMPLE REGION

Stage/Nutrients	Seedling stage (1-3 weeks after planting) mg/kg	Vegetative growth stage (3-6 weeks after planting) mg/kg	Reproductive stage (6-12 weeks after planting) mg/kg	Maturity stage (12-16 weeks after planting) mg/kg
Nitrogen (N)	20-50	50-100	100-200	100-200
Phosphorus (P)	5-10	10-20	20-30	10-20
Potassium (K)	50-100	100-200	200-300	300-500

TABLE IV. STAGE WISE NPK THRESHOLD VALUES FOR A SAMPLE REGION

Stage/Nutrients	Seedling stage (1-3 weeks after planting) mg/kg	Vegetative growth stage (3-6 weeks after planting) mg/kg	Reproductive stage (6-12 weeks after planting) mg/kg	Maturity stage (12-16 weeks after planting) mg/kg
Nitrogen (N)	25	75	150	150
Phosphorus (P)	6.5	15	25	15
Potassium (K)	60	150	250	400

Step2: we propose one NPK sensor for every 2500 Square meter (approximately 4 per Hectar). This will ensure target specific localized treatment i.e., X place may contain Nitrogen Deficiency, Y place may have some other Deficiency etc.,

Step3: The client ESP32 controllers gather these values and send to the cloud.

Step4: The server ESP32 Read these values and apply inferences using the developed machine Learning model and send the status of deficiency/ correction to the cloud as well as farmer APP.

Phase 2 uses the same procedure.

2. Phase3 Procedure

Step1 : Leaf and associated disease features are used to develop Machine learning model and deployed in Server ESP32.

Step2: Farmer send the leaf images on regular periodic basis (weekly once) to the cloud Database through the Mobile APP.

Step3: Server ESP32 read the image data from Cloud and perform inferencing with the model and send findings to the farmer using Cloud and Mobile APP as shown Figure 7.

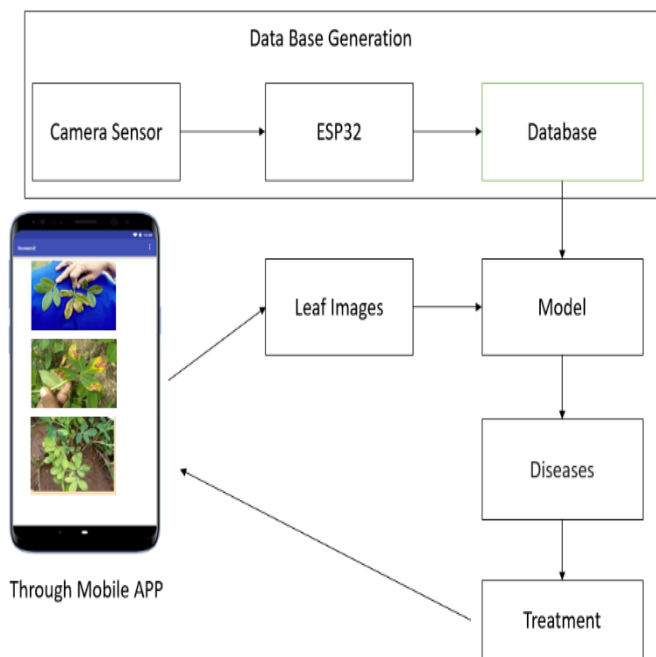


Figure7. Early-Stage plant disease detection model

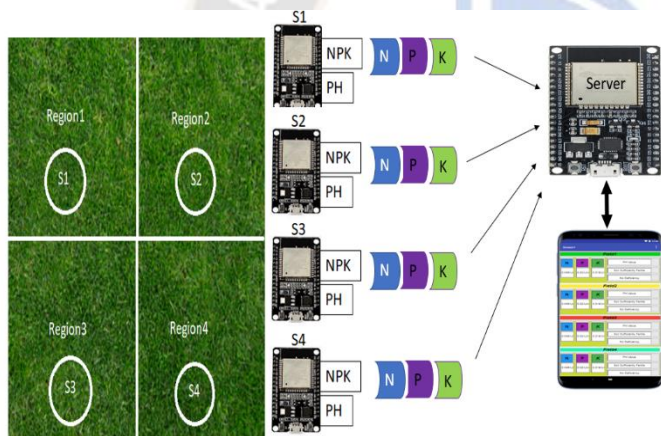


Figure8. Field Division and Sensor Development

#### IV. EXPERIMENTATION

The NPK sensor using MAX485 and PH sensors are interfaced to ESP32 DEV Module. Driver Input (DI), Driver Enable (DE), Receiver Enable (RE) and Receiver Output (RO) of MAX 485 are connected to the GPIO pins 16,17,18,19 respectively. The PH sensor is interfaced using PH sensor signal board A0 is connected to GPIO Virtual Pin. 12V and 9V rechargeable batteries are used for to provide power supply to the respective sensors. OLED displays are used for local interaction. As the virtual pin contains built in 12-bit ADC calibration is needed for sensor analog value. Analog output of the sensor is multiplied by factor (3.3/4095). Nutrient values and PH value is obtained on real-time basis with appropriate program scheduling. Any Android OS Smart phone with considerable picture resolution is allowed for image capture and communication with our framework. Four such modules having necessary Libraries are deployed in one hecter agriculture field shown in Figure 8. The sensed data is sent to Google Firebase cloud for once in a day. Server ESP32 retrieves these values from cloud and send to Random Forest classifier-based inference engine. The inferencing model is then detecting nutrient deficiency as well as early detection of Leaf deceases. This information is then shared with farmer using appropriate notifications through mobile APP. Sample pseudocode is illustrated below for computing inferencing process.

TABLE V. ESSENTIAL PART OF PSEUDOCODE

```
# Input: NPK sensor readings
nitrogen_reading = read_nitrogen_sensor()
phosphorus_reading = read_phosphorus_sensor()
potassium_reading = read_potassium_sensor()
Inference Model ()
# send to inference engine
# Based on the values inference engine identifies Nutrition deficiency
if nitrogen_reading < THRESHOLD_NITROGEN:
    deficiency = "nitrogen"
elif phosphorus_reading < THRESHOLD_PHOSPHORUS:
    deficiency = "phosphorus"
elif potassium_reading < THRESHOLD_POTASSIUM:
    deficiency = "potassium"
else:
    deficiency = "none"
Treatment (N,P,K values)

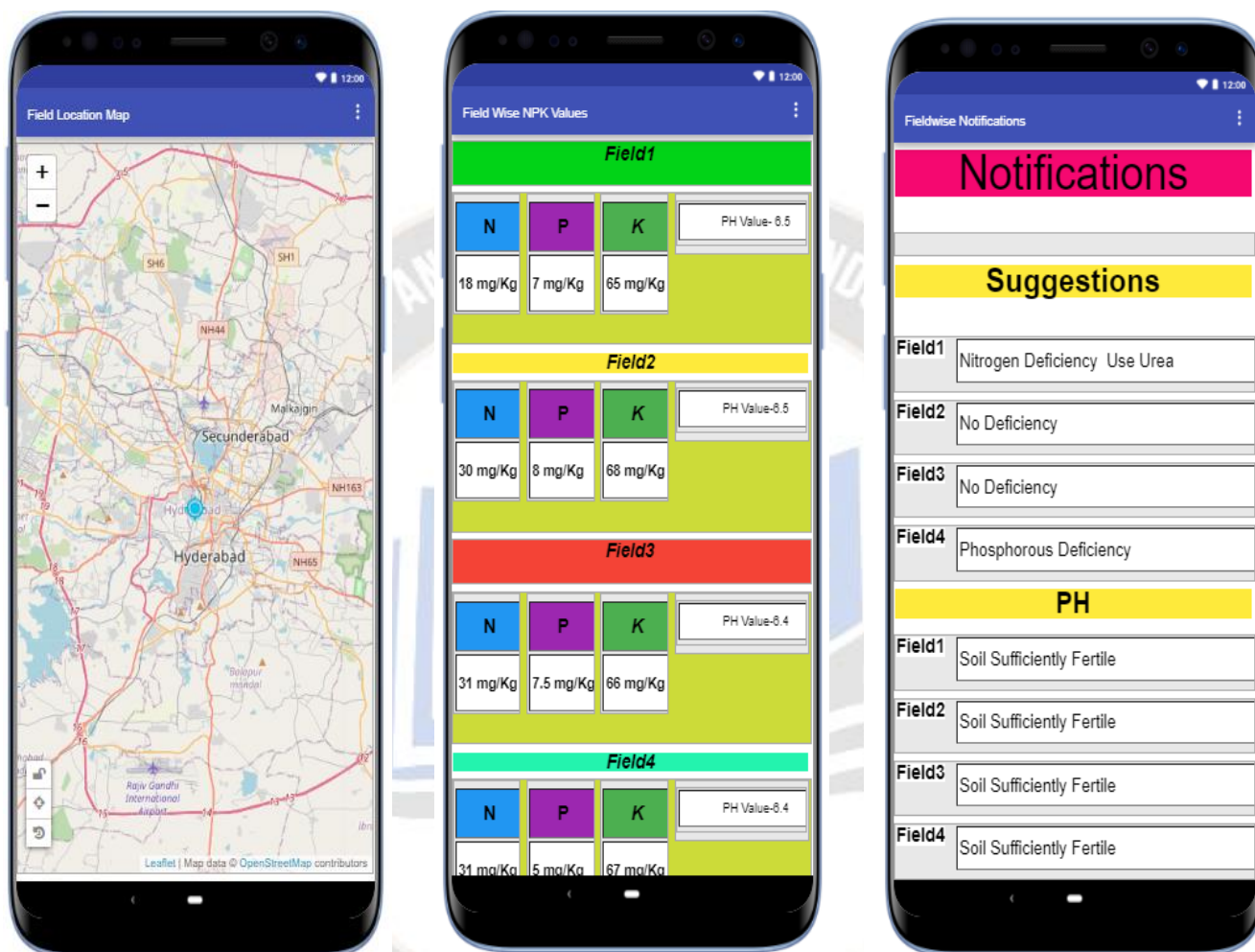
# Output: Report nutrient deficiency (if any)
if deficiency == "none":
    print("No nutrient deficiency detected.")
else:
    print("Detected a deficiency in:", deficiency)
```

#### V. EXPERIMENTAL RESULTS

Figure 9 (a) denote the Google map associated with the cultivated area. Further, Stage1 soil nutrients and PH values are

pushed into the mobile APP. It is observed that field1 has 18 mg/Kg Nitrogen, 7 mg/Kg Prosperous, 65 mg/Kg Potassium with PH value 5.5 as shown in Figure 9(b) . Since The Nitrogen value is less than the Threshold 25 mg/Kg. This deficiency is notified as an alert to the farmer along with the suggestion as

indicated in Figure 9(c). Remaining fields of stage1 are also available in the figure 9.



(a) (b) (c)  
Figure 9. a) Google map of Experimental area b) Nutrient Values c) Alerts

TABLE VI. FIELD WISE SENSED VALUES AND CALIBRATED SOIL NUTRIENT VALUES

	Field1		Field2		Field3		Field4	
	Sensed Value mg/Kg	Calibrated Value Kg/Hector	Sensed Value mg/Kg	Calibrated Value Kg/Hector	Sensed Value mg/Kg	Calibrated Value Kg/Hector	Sensed Value mg/Kg	Calibrated Value Kg/Hector
N	18	27	30	45	31	46.5	31	46.5
P	7	10.5	8	12	7.5	11.25	5	7.5
K	65	97.5	68	102	66	99	67	100.5



### 1. Calibration Process

The sensor values are calibrated with the following procedure for calculating NPK values in Kg/Ha.

- (i) Calculate the Mass of sample area:  

$$\text{Mass}(M) = V * \rho \quad (5)$$

Where, V is Volume

$\rho$  is Bulk Density (for sandy clay loam soil is 1500)

$$V = A * D \quad (6)$$

where A is Area (1Ha=10000 m<sup>2</sup>)

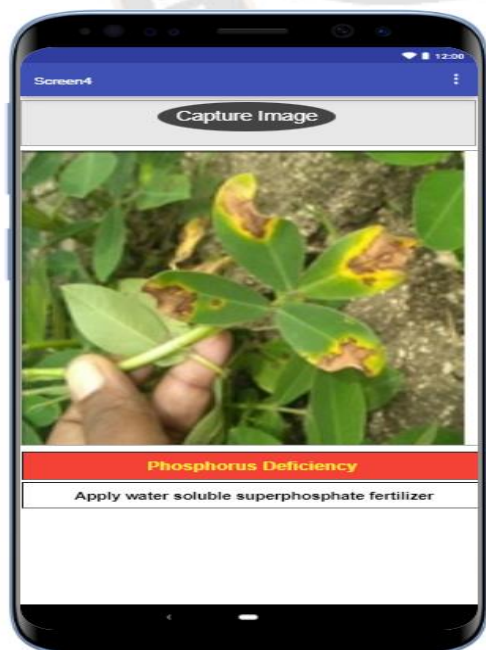
D is Depth (10 cm = 0.1 m)

- (ii) N/P/K value obtained from sensor:  
 Let r will be sensed value.  

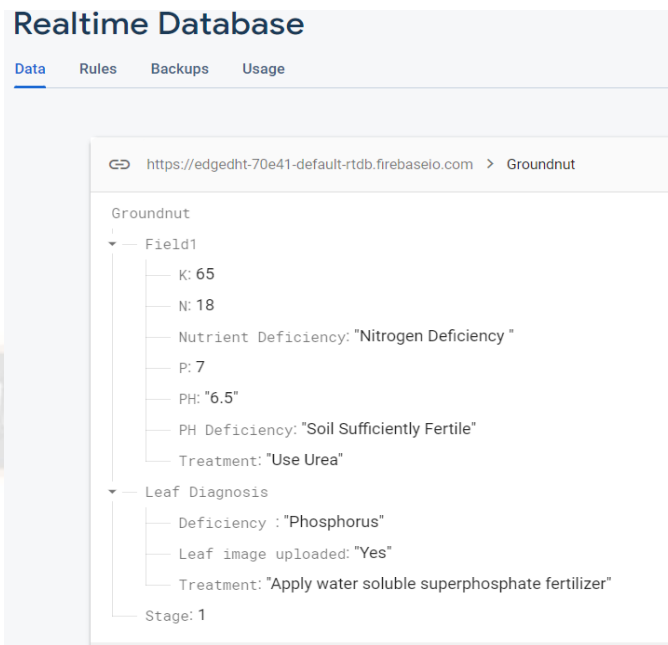
$$\text{Estimated N/P/K value} = r * M \quad (7)$$

The Table VI reveal actual and calibrated values.

The real-time database project firebase console <https://console.firebase.google.com/project/edgedht-70e41/database/edgedht-70e41-default-rtdb/data/~2Fgroundnut> is developed for supporting cloud interaction in our framework. Figure 10 (a) reveals the processed Groundnut leaf image of phase 3 send by the farmer. The inferencing model detects phosphorous deficiency and alert the farmer further remedial action. Figure 10 (b) reflects the Google Firebase cloud containing information about stage1 soil nutrients, PH value and Leaf Diagnosis of phase3. The figure also incorporates alerts and suggestions.



a)



b)

Figure 10. a) Groundnut Leaf Image Diagnosis b) Firebase Console Realtime Database

### VI. CONCLUSION AND FUTURE SCOPE

The frame work developed will be handy for remotely analysis of fertility of soil, PH value and early-stage disease detection of groundnut crop. The proposed approach makes the farmer self-reliant in detecting the soil Nutrients such as Nitrogen, Phosphorus and Potassium and prevent over/ under fertilization during groundnut crop cultivation. The segregation of soil while deploying the sensors enable region wise Sub-Field analysis. Field wise NPK/ PH sensors are able to resolve the issues associated with solitary sensor present in the entire field and improves the framework reliability. Futuristic Drone based technologies along with our proposed framework provide the capability of need-based Pest spraying in the auto irrigation.

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