Soil Nutrients Analysis Techniques and Crop/ Fertilizers Prediction- A Review

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***Abstract*—Soil analysis is an integrated part of precision agriculture to improve the efficiency of the farm in the agriculture sector. In addition to the time- and money-consuming conventional chemical analysis method, technological improvements have given rise to numerous novel approaches to measuring soil characteristics. The principle of maximum optical absorption of visible light by material in a particular frequency region due to the movement of electrons is applied to get information about critical soil nutrients i.e., NPK. Real-time soil parameter monitoring systems are created with the assistance of the improved sensors integrated with the Internet of Things. The cost-effectiveness of determining soil properties is increasing due to advancements in MEMS technology. Collection of the data about soil nutrients (NPK) and other parameters (temperature, pH value, ground cover percentage, etc.) with the assistance of machine learning algorithms such as decision trees, CNN, and regression helps in the building of an efficient prediction system related to crops and fertilizers. Digital image analysis with CNN is a noteworthy way to monitor already grown plants and predict the appropriate amount of fertilizer.**

Keywords*— Soil Analysis, Soil Nutrient, Cantilever Beam Sensor, Spectrophotometry, MEMS, Machine learning, NPK detection, Optical Sensor, Machine Learning, Non-invasive, Decision Tree, Random Forest Classifier, SVM.

I. INTRODUCTION

Agricultural sector is one of the oldest and most important economic sectors in the world. This sector is crippled by the lack of awareness, resources, and improper infrastructure in most third-world countries. These factors lead to more severe problems like less yield of the land, farmer suicides, an economic downturn for farmers, etc.

All these problems originate at one point i.e., the less yield of the crop, which is directly related to three main nutrients of the soil. Nitrogen, Phosphorus, and Potassium; are collectively known as NPK. Nitrogen is responsible for the formation of proteins and tissues in the plant, Phosphorus is pivotal for storing energy and the process of photosynthesis, and Potassium provides immune resistance to the plant. Different varieties of crops need these nutrients in different amounts for proper growth. Also, in case of any nutrient deficiency, a proper fertilizer can be used.

The measurement of the NPK values by traditional chemical analysis is time-consuming and cost-ineffective for the farmers. But with the advancements in sensor technology, one can get the values of NPK in real-time with the help of advanced sensors [1]. But the cost of these systems and long-time maintenance issues are still faced here. The novel method to calculate these values is based on the principle that nutrients optically absorb light [9][10][11][12][15].

MEMS-based devices can be a new and efficient alternative to the sensors for measuring soil parameters [17].

A. MEMS-Based Sensor

In optoelectronic devices, the MEMS-based sensor provides great sensitivity and minimal implementation. The cantilever beam sensor is based on the idea of local heating brought on by the targeted nutrient-absorbing light. A bi-material configuration is employed in the design of the cantilever beam. The cantilever beam bends as a result of strains felt in the shaft brought on by the materials' thermal expansion. This beam bending is used to compare the thermal expansion-induced bending to the concentration of the targeted nutrient in the soil.

Around 0.1–5% of the total plant biomass is made up of the nutrients in the soil sample. The remaining portion of the plant biomass is made up primarily of minerals like oxygen, hydrogen, and carbon. Depending on the quantity of each nutrient required for plant growth, the nutrients can be divided into macronutrients and micronutrients. Considering their inadequacies are more prevalent in the soil than those of secondary macronutrients, nitrogen, phosphorus, and potassium are referred to as primary macronutrients. Together, these three nutrients are referred to as NPK nutrients.

B. *Applications of Machine Learning*

In computer science, artificial intelligence (AI) is also alluded to as machine intelligence since machines may be programmed to accomplish tasks analogous to those of the human brain. Here, artificial intelligence (AI) is defined as the study of how various algorithms can be employed and laid out to analyze and extract knowledge from data. The term "Computational Intelligence" is a broad concept that refers to a wide range of disciplines including pattern recognition, probability theory, statistics, machine learning, and numerous approaches like fuzzy models and neural networks. Analytical techniques including classification, regression, predictions, and optimization approaches are used in myriad applications.

Algorithms like supervised, unsupervised, and reinforcement learning are the main emphasis of machine learning, and each of them has advantages and limitations. When using supervised learning, an algorithm constructs a mathematical model using a set of data that encompasses both the inputs and the desired outputs. A method that uses unsupervised learning builds a mathematical model from a set of data that only contains sources and no identifiers for the expected outcomes. Agricultural data is being evaluated using machine learning techniques. This data is exported in different formats to analyze and visualize the obtained results [10].

The dataset used to train the computer for better classification results must be of high quality and quantity for machine learning approaches to be successful. Following the processing of those visuals, the data was divided into four classes (less Nitrogen=N, fewer Phosphorus=P, less Potassium=K, and NPK) to train the system to forecast fertilizer application using a decision tree technique [7][8].

A method to evaluate nutrient deficiency in crops was proposed in 2018 and then again in 2020. It is essential to produce food with the required ratio of nutrients. To ensure agricultural yields, Phosphorus (P), Potassium (K), Organic Carbon (OC), Boron (B), and the pH level of the soil are taken into consideration. The remedy to these five nutrient classification issues was presented using the Extreme Learning Machine (ELM). The accuracy of the calculations for the proportion of four out of the five nutrients found within the soil was 80% [7].

The process that Machine Learning algorithms often use is a quantitative approach (data collection), computation (data processing), and training and testing of data samples. Based on prior trends and the kind of soil, a classification algorithm like SVM can be used to predict crops and classify soil. The following datasets are essential for the project: There are features in the soil dataset with varied chemical characteristics.

Some of the algorithms that are used in Soil prediction and classification are:

- Logistic Regression: A dataset with one or more exogenous factors is evaluated using this technique, and observations are delivered. To anticipate the optimal relationship among the dependent and free elements, the Logarithmic Regression model is used.
- Random Forest: This methodology employs a democratic framework to determine the class in a given situation.
- Support Vector Machine: The goal of this approach is to construct a decision boundary, also known as a hyperplane, that can divide n-dimensional geometry into classes and make it simple for future data points to be placed in the pertinent category.

II. METHODOLOGY

The soil analysis pivotally depends on the measurement of factors such as temperature, humidity, pH value, and NPK nutrients. The values of these parameters are used to map the prediction and monitoring system.

There are numerous techniques to measure the nutrient content of the soil.

The papers "Soil NPK Levels Characterization Using Near-Infrared and Artificial Neural Network" [10], "Detection of NPK nutrients of a soil using Fiber Optic Sensor" [12], "Automation of soil nutrient monitoring system and irrigation control" [11], "Primary Nutrients Determination in the Soil Using UV Spectroscopy," [9], and "Optical Sensing of Nitrogen, Phosphorus, and Potassium: A Spectrophotometrical Approach Toward Smart Nutrient Deployment" [14] are primarily concerned with the crucial idea of nutrient quantification and detection based on the enhancement of light absorption. The concept here is that every material consists of atoms hence electrons. Electrons vibrate at specific frequencies hence at a specific wavelength. At this wavelength, the electrons absorb the maximum light energy and start to vibrate. This results in a change in energy levels and with help of this deviation the values of the nutrients are being calculated.

Apart from all these methods, the paper [15] Sensors & Transducers Simulation of a Cantilever Beam Based Soil Nutrient Sensor proposes a novel method of measuring the nutrient value using a MEMS-based cantilever beam. The concept of measuring the optical absorption of light here is similar in [9][10][11][12]; but here the values are obtained by observing the deviation in the cantilever beam which is caused by localized heating by the absorbed light.

The concentration of the desired nutrient in the soil and the bending brought on by thermal expansion can be related using the deviation of the MEMS-based cantilever beam. The cantilever beam consists of a beam fixed on one end and frees on the other end. The cantilever is allowed to bend through different techniques as required concerning a parameter being measured [15]. MEMS-based devices are an important alternative to traditional sensors due to their small size and low power consumption [17].

The main parameters for MEMS sensors in agriculture involve humidity sensors, temperature sensors, moisture sensors, and photosynthetic radiation sensors. Photosynthetic

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sensors are used for measuring the amount of light required for plant growth. Photosynthesis requires light in the 400 nm-700 nm wavelength. Photodiodes that are sensitive in this region are used. Moisture sensors consist of a water-sensitive nano-polymer on a cantilever beam and an on-chip temperature sensor.

The MEMS sensors which use ISFET (Ion-selective field effect transistor) for the detection of macronutrients in soil have an ion-selective film on top of them. A potential is developed in the interface between the ion-selective film and the FET (Field Effective Transistor) when the target ion encounters the film. This potential is a function of the concentration of the targeted nutrient. The issue with such sensors is that a need for a separate ion-selective film is required for each nutrient. This means that a separate structure is required for each nutrient. In this paper, the simulation of a model for a MEMS-based soil nutrient sensor that can be used for detecting all three NPK nutrients is done. This model is stationed on the Optical Absorption of light by the targeted nutrient.

The COMSOL Multiphysics software platform is used to do the simulation of the proposed model. Here the ‘Heat transfer model’ of physics is applied to get simulation and the ‘Stationary’ model is applied to do final computing. The cantilever beam has two layers 1000 µm long. The top layer is Aluminum and the bottom layer is Silicon Oxide [15].

To apply Thermal Expansion, the temperature of the fixed end of the cantilever beam is kept to be at 293.15 K and the free end at 294 K. The temperature gradient and contour temperature were observed across the beam. The deviations are noted.

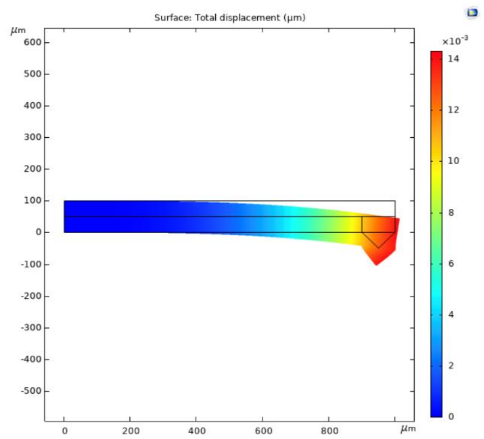

Fig. 1. Cantilever Beam Simulation in COMSOL Multiphysics

The construction of the mechanical sensor mentioned in the paper [15] is based on Bi-material Cantilever Beam and is explained in detail in the paper [10] “Evaluation of Bi-material Cantilever Beam for heat sensing at atmospheric pressure”. The implemented bi-material cantilever beam was meant for use in chemical and biological applications. The main construction of the cantilever beam was made from a low-stress SiNx film measuring 0.9x1, and it was then coated in an Au layer. Since the cantilever beam was intended to be employed in the bending mode, its length and thickness are in the micrometer and nanometer ranges, respectively. 400 nm thick, 20–70 m long, and 400 m wide cantilever beams were used for this project. Starting with a 300 m thick silicon wafer, the fabrication process was initiated. A 14110 nm thick SiO_2 layer was produced on a silicon wafer by wet thermal oxidation, and a 3032 nm thick SiN_x layer was synthesized on the SiO_2 layer by low-pressure chemical vapor deposition. Very thin Cr and Au layers were deposited on top of the SiN_x layer by thermal evaporation at rates of 1.7 and 0.6 nm/s, respectively. The Au layer was 90 nm thick and a 5 nm thick Cr layer was used to improve the adhesion between the Au layer and the SiN_x surface.

The SiN_x layer was removed using electrical discharge, Reactive Ion Etching (RIE), which makes use of CF_4 and O_4 gases. SEM was used to capture a picture of the bi-material cantilever beam (SEM). The cantilever beam is curved upward as depicted in the image below as a result of the uneven residual stress strains in the numerous layers that make up the beam. The bi-material cantilever beam was positioned on one side of the device and examined under a microscope while a small area at the free end of the device was exposed to laser diode radiation. The device for the experimental setting was the Microsystem Analyzer MSA-500, manufactured by Polytec in Germany [20].

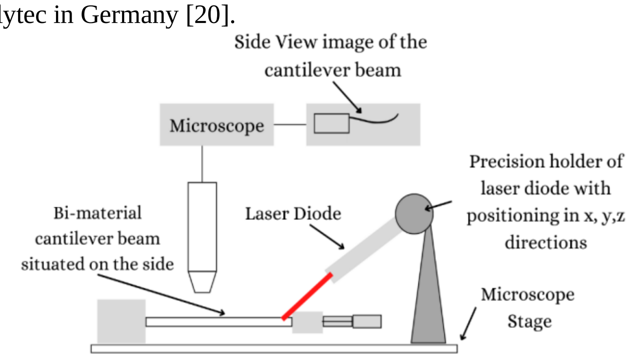

Fig. 2. Experimental layout of the Cantilever beam heated at the tip with a Laser Diode.

The Here, the laser diode’s heat spot was concentrated on the little dorsal surface of the cantilever that was next to the micro platform. The system’s video camera captured the cantilever beam’s curvature. A micrograph of the cantilever beam was obtained from the side, and heated by a laser diode at its free tip for this study. The laser diode’s output power ranged from 0.52 to 13 mW when the experiment’s cantilever beam was suspended in the atmosphere. By changing the laser diode’s operating current, the capacity factor was tweaked. The same modifications in laser power were employed for the case where the cantilever beam was suspended in a vacuum. Since the bi-material cantilever beam was initially coiled due to residual tension that exists in the composite materials, the instantaneous overheating of the cantilever beam that results from the increase in laser diode power from 2.5 to 5 mW in this case irreversibly destroyed the cantilever beam. The curvature’s radius was 410 m at a temperature of 25 °C. Whenever this cantilever beam was evaluated in the vacuum, the 5mW laser power that was released caused damage to the cantilever beam, resulting in severe internal stress and a substantially reduced cantilever beam radius of 410 to 165 µm.

A cantilever beam can also be used in the application of thermal sensors [19]. The working principle of the resonator

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cantilever beam temperature sensor is based on the shift in resonant frequency in response to temperature changes. The resonant frequency and the temperature coefficient were 960 kHz and 22.0 ppm/K, respectively. Generally, for high thermal stability electron devices, such thermal effects should be adjusted. Higher reliance on temperature fluctuations is more predictable from the perspective of thermal sensing. A straightforward calorimeter can be created using a mono-material cantilever. However, due to its temperature coefficient, which for Si is 35 ppm/K, its sensitivity is constrained. The bi-material cantilever beam calorimeter (CBC) is a composite made of metal and silicon nitride in the form of thin layers. The CBC material can be utilized in a variety of contexts. Both external factors and catalytic processes occurring directly on the cantilever beam surface have the potential to affect the cantilever beam's heat flux. The calorimeter has a microheater that allows incendiary vapors to self-ignite to detect explosives and combustible compounds. The ignition, which originates at ambient temperature, is examined using the cantilever beam resonance or bending. The cells are suspended close to the cantilever beam tip in biological applications, such as monitoring the temperature of a single cell or a small group of cells, causing the heat to be concentrated only at the cantilever beam tip. The optical transmission reflection method is frequently used to calculate the cantilever's deflection. An interferometer with white light is more beneficial than one with a single laser. Another method for tracking deflection in the cantilever beam is piezo-resistive detection with strain gauges [1].

The color of the aqueous solution can also be the detection parameter, especially for the presence of nitrogen [16]. The methodology is followed up like;

1) Production of Aqueous Solutions: Natural soil samples are well combined and agitated with 0.1g of calcium sulfate, deionized water, and small amounts. Finally, the solution is augmented with the components of the NitraVer 5 (reagent) powder pillow.
2) Color Detection: A microcontroller and a color-detecting sensor are used to determine the aqueous solution's color. The expected separation between the soil sample and sensor is 3 mm at most. The sensor, which can more precisely determine the concentration of the solution's color, consumes the white light that is reflected by the solution. This aids in calculating the amount of nitrogen present. The sensor converts analog readings to digital signals and transmits the resulting electrical signal of (R, G, and B) values to the microcontroller to function as an IoT device.
3) Conceptual Architecture**:** It is made up of a color-detecting sensor and powerful LED lights that are employed with various wrappers to evenly disperse and reflect light. Here, a constant gap of 3 mm was maintained between the sensor's photodiodes and the liquid solution. The output became less exact as the distance increased, and light diffusion resulted from a decrease in distance. Since the LEDs' emission spectrum is rather limited, direct intensity modulation is also an option for these LEDs. This architecture is intended to calculate the RGB value using a 2% flicker rate. In contrast to the usual practice of using a gradient on the comparator, discrete values are employed in this study so that the color sensor can more precisely confirm the existence of nutrients.

The novel and cost-effective way to get NPK values are by applying the principle of maximum optical absorption by material. By observing the variations in the near-infrared region (1240nm-1480nm) for soil samples and mapping them using regression analysis, one can get the NPK values with 99.8% accuracy [10]. Here, 50 samples of soil having different NPK values were collected. The samples were air-dried, cleaned, and stored in sealed containers. The light absorbance of each sample was recorded using a locally developed instrument which was calibrated using Foss NIRS Model 6500. A spectrometer's 60mm petri dish was filled with a 100-gm soil sample. A rotating sampling pool contained the dish. To calculate the NIR absorption spectra, the NIR absorption peaks of each scanned sample were identified. The spectral range here was 900nm-1700nm. The absorbance characteristics of soil samples were observed. Subsequently, the peak value for each was obtained. Peak absorbance wavelengths range from 1240nm-1480nm for all samples. The absorbance wavelength of the soil sample was calculated using this data. The peak absorbance value for each sample was mapped with the known NPK concentration. Dataset analysis was done using a Neural Network in MATLAB R2017b. 50×8 (50 soil samples × 8 NIR characteristic absorbance wavelengths) input data is needed to get 50 × 1 (50 soil samples × NPK level) output or target data. Dataset was divided into 3 parts- 70% for training, 15% for testing, and 15% for validation. Ten neurons were employed in the Levenberg-Marquardt backpropagation technique to train the network. Cross-validation was employed to enhance fitting effectiveness and prevent over-fitting. The combination of an optical sensor with a spectrograph is a potent way to get the accurate value of NPK.

The transmission system and the detecting system are the two mechanisms used in the development of the optical sensor [12]. Direct measurement of NPK nutrients in the soil using spectroscopy that combines an LED light source and photodiode detector (along with a signal processing circuit and a clear polyethylene terephthalate container). A multimode plastic fibre optic sensor with seven fibres that are stacked in a concentric shape and six fibres that are transmitting fibres has been developed. The frequency, patterns, and duration of the photoluminescence are all controlled by the microcontroller used to create a square wave signal.

The luminosity and the nutritional sample are in direct contact. The residual light from the absorption of nutrients, which has a peak wavelength of 850 nm, is received by the Si Photodiode, and transformed into a photocurrent. To convert the signal to a proportional voltage, signal conditioning uses a low pass filter to pass the modulation frequency of 1 kHz and a high pass filter to block the noise frequency, which is typically at 120 Hz.

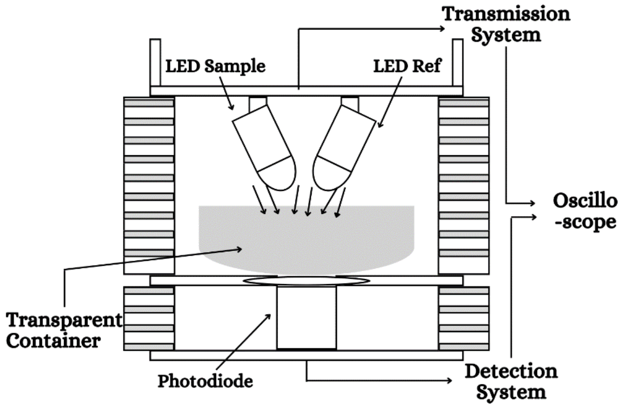

Fig. 3. Schematic diagram of Vertical Construction of NPK nutrient of soil Optical Sensor.

There is a similar approach to getting information about soil nutrients by utilizing LED and LDR, and by applying Beer-Lambert's law. In addition to that, an automatic irrigation system depending on soil moisture level with Bluetooth is also integrated here [11]. Here the model is divided into two parts. The first part is for the soil nutrient measurements and the other one is for an irrigation control system. The microcontroller's machine cycles are used by these components in parallel, and a Bluetooth module transmits the results to a mobile device. The optical transducer is provided with three wavelengths within the first phase, where nutrients absorb most efficiently (N, P, K). The intensities are measured by LED and LDR. The differences in voltage values across LED and LDR are applied while calculating the amount of light absorbed.

By using Beer-Lambert's law, the concentration of NPK is estimated[12].

$$A_{npk} = -\log\left(\frac{V_i}{V_o}\right)$$

Where, V_i: Voltage across LDR
V_o: Voltage across LED

The data are compared by a microcontroller with two threshold levels viz threshold 1, and threshold 2. These threshold levels are set at runtime depending on the type of parameter being used, and values are categorized as low for absorption values below threshold 1, medium for absorption values between threshold 1 and 2, and high for absorption values over both threshold 1 and threshold 2. For additional processing, Bluetooth sends these values to Android. In the second phase, the soil moisture sensor gauges the soil's moisture content using the conductivity principle. The voltage drop across the sensor varies according to water content resistance, and this voltage drop is used to calculate fluctuations in water content. A microcontroller processes this value before sending it through Bluetooth to the application. Once more, the measured value is collated to a threshold value, which represents the ideal amount of water required for a plant's healthy growth, and if the measured value is lower than the threshold, the farmer is alerted to activate irrigation. In the hardware implementation of this paper, the test tube containing soil solution for testing is kept between 3 LEDs of colors RBG corresponding to the maximum value of NPK nutrients resp and 1 LDR which have formed an optical transducer. This whole setup is fully covered. The microcontroller's input and output analog pins are connected, respectively, to an LED and an LDR. Beer-law Lambert's is used to monitor the absorbance level of each nutrient while LEDs are sequentially activated. A soil moisture sensor detects the amount of water in the soil concurrently.

Another research evaluated spectral intervention between N, P, and K in simulated fertilizer solutions and the concomitant detection limits to carry out assays to show the viability of measuring NPK [14].

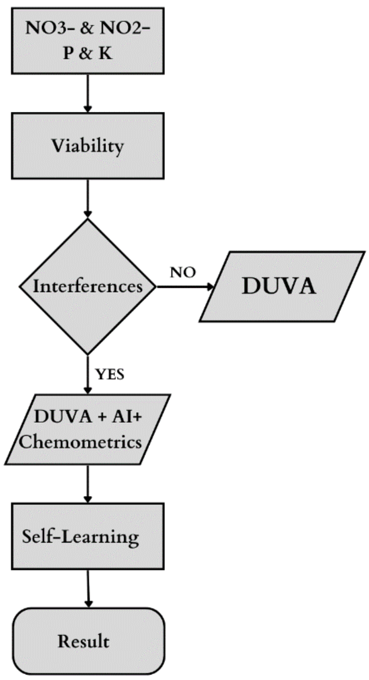

Fig. 4. Workflow for Nitrite and Nitrate Assessment. Direct UV Assessment (DUVA)

The prototype is made possible by combining optical-based sensors with optical fibres, taking advantage of their well-known benefits such as corrosion resistance, electromagnetic immunity, and remote manipulation. A bulky desktop system was built using a D2 (deuterium) light source (Ocean Optics model DH-2000-BAL), a spectrometer (Ocean Optics model HR4000), a transmission optical fibre bundle (UV), and a stainless steel slitted reflective probe for insertion on materials. Before analyzing the sample, stock solutions were created and used throughout the test. To produce various ionic species concentrations, various volumes of the stock/tank emulating solutions were utilized (target). The solutions were produced in tiny glass bottles, and then the reflection probe was incrementally placed to reduce the presence of air. For an integration time of 60 ns, 10 scans were used for data gathering. The spectra that were acquired are a superposition of interference and scattering caused by the individual constituents' varying absorption spectra. An initiative that takes a gander at spectral characteristics that better match a covariance direction between the characteristic interference of the spectra and composition is preferable to a "monolithic" model, such as models that resemble local-partial

Least Squares (PLS), Support Vector Machines (SVM), and Deep Learning Artificial Neural Networks (ANN), which postulate that there is a covariance mode that relates both with high precision and accuracy. Singular value decomposition, Fourier, or Wavelets are examples of decomposition techniques that can be used to extract characteristics from the original data. These attributes are then extracted from the original data and the actual data is reconfigured into a compressed space of significant features. These tests used the direct UV assessment (DUVA) of both nitrates and nitrites (abs max = 302 nm and 352 mm, respectively). No sulfide [3], bromide [4], or organic matter [5] interferences were found. To find any potential interferences within the selected components, a set of eight tests was evaluated. The figure depicts the planned approach to identifying first evaluations and interferences.

Paper [9] reviewed the different types of technologies present for determining the nutrients present in the soil. The results of UV spectroscopy are discussed in detail along with remote sensing and on-field sensing. The main objective is to analyze soil properties for accurately mapping various primary nutrients [9]. Numerous soil samples from farms in Pune (Maharashtra, India) were tested for analysis of the primary nutrients using techniques such as UV Spectroscopy. The entire process will be carried out using some chemical methods.

The same principle of the optical absorption method is furthermore cost-effective with the help of optical transducers [3]. The paper mentioned various NPK sensing techniques currently available or have been developed and a comparison has been drawn with the Optical transducer. There has also been a reference to the future scope that might flourish in the future. Firstly, a conductivity measurement technique is introduced where a color change due to the concentration in the electrodes dipped in the given soil samples causes a change in the conductivity which can be converted into electrical signals for analysis. The second approach listed is the fibre optic sensor, which features a configuration of source and receiving fibres. The third technique is the soil spectroscopy technique which makes use of LED and fiber optic cable. Matching wavelength is used to detect the type of nutrient in the soil. Out of all these techniques, Optical transducers are more economically viable due to readily available components. The experimental analysis was done per the guidelines of the Department of Agriculture of the Philippines government to reduce any erroneous results. A composite of ten separated soil samples was taken from the subjected area and the said sample undergoes the quartering method to reduce sample mass. The proposed system includes hardware, software, and a mobile application. Hardware components include LEDs, an LCD, a photodiode sensor, and a NodeMCU ESP8266. The sensor and optical transducer readings are sent to the ESP8266 which analyzes them and displays the N-P-K values on the LCD. Further integration of mobile applications has been suggested for the ease of farmers so that they can access the readings via mobile phone applications in the presence of Wi-Fi connectivity. The system was developed for a particular crop here which is corn.

Similarly to this, the paper [8] similarly concentrates on maize plants as a single crop. To determine the appropriate sorts of fertilizers to employ, the study "Predicting Fertilizer treatment of Maize using Decision Tree Algorithm" investigates the 'Ground Cover Percentage' metric. Here, Digital image analysis is implemented to obtain the value of the ground cover percentage and that value is the input parameter for the decision tree. The results were analyzed with the help of a confusion matrix. 2×2 feet image frame size is fixed for the digital image analysis. The maize crop's top perspective should be used to take the image. To predict the crop health conditions the whole dataset was classified into two categories according to the number of leaves (3 and 6). The Green Pixels are evaluated using the image analysis program "Can Eye" (Ground Cover Percentage). A total of 245 occurrences from the International Maize and Wheat Improvement Center (CIMMYT), Bangladesh, had their raw data (fixed-size photos) collected. These images were converted into fixed-resolution images.

$$Ground\ Cover\ Percentage\ (\%) = \frac{Total\ Green\ Pixels}{Total\ Pixels} \times 100$$

.One of the most well-liked supervised machine learning techniques, called a Decision Tree (DT), continuously divides the data into categories based on specific factors. Decision nodes and leaves, which make up the tree's two fundamental aspects, can be understood. The "Information Gain" method is employed by this algorithm to choose the proper root node.

$$Information\ Gain\ (S,x) = Entropy(S) - \sum_{v=x} \frac{|S_v|}{S} + Entropy\ (S_v)$$

As a root node, choose a node with a higher Information Gain characteristic. Information Gain is calculated using another feature known as "Entropy."

$$Entropy(S) = \sum_{i=1}^{n} (-P_i log_2 P_i)$$

The Decision Tree is a straightforward algorithm with an easy implementation, which is why it was selected. These kinds of datasets adapt well to the decision tree method.

The nutrient deficiency in maize plants can be detected using Convolutional Neural Networks [7]. CNN's are a class of Deep Neural Networks that can recognize and classify particular features from images and are widely used for analyzing visual images. CNN is very useful as it minimizes human effort by automatically detecting the features.

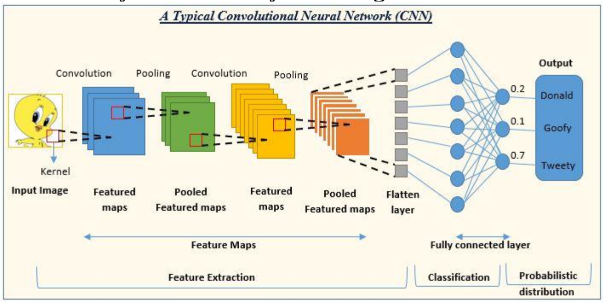

Fig. 5. Overview of Convolutional Neural Network (Analytics Vidhya 2022)

The convolution layer is the core component of CNN. It carries a significant proportion of the network's computation power. The kernel—a group of trainable parameters and the limited region of the perceptron is two matrices that are combined in this layer to form a dot product. The kernel is deeper yet smaller in space than an image. The pooling layer replaces the output of the network at certain locations by

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deriving a summary statistic of the nearby outputs. This helps in reducing the spatial size of the representation, which decreases the required amount of computation and weights. Neurons in the fully connected layer have full connectivity with all neurons in the preceding and succeeding layer as seen in regular CNN. Therefore, it can be computed as usual by a matrix multiplication followed by a bias effect. The Fully Connected layer helps to map the representation between the input and the output [2].

Images of nitrogen-deficient, phosphorus-deficient, and potassium-deficient maize leaves make up the training dataset. The trained model is formed after the training set has been run through the CNN layers. Based on the features it learned during the training phase, this model was able to recognize the type of nutrient inadequacy in the test image. The kind of nutritional shortage in maize leaves is successfully determined. Here, the Inception V3 CNN model is applied for feature extraction. Training data is divided into 3 parts, i.e., 80% training set, 10% validation set forms, and the remaining 10% testing set. Softmax regression is used to train the dataset.

The proofs acquired from visuals are employed to generate the probability. By using pixel intensity, the proofs are retrieved.

$$evidence_i = \sum_j W_{i,j} x_i + b_i$$

$$y = softmax(evidence)$$

$$softmax(x)_i = \frac{\exp(x_i)}{\sum_j \exp(x_j)}$$

Where Wi indicates weights, bi represents bias and j is for the input pixel summation index [7].

Here is a complete flowchart

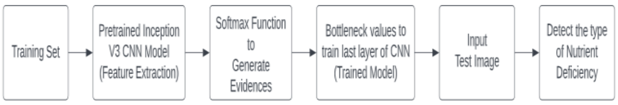

Fig. 6. Methodology for Nutrient Deficiency Detection

The working methodology for identifying soil characteristics including pH, temperature, and precipitation utilizing the sensor network design is also explored in the paper [1]. At first, a sensor device is used to capture all the relevant information about the soil contents. The soil sensor when connected to a mobile device via a USB cable will make use of an application to organize the relevant data by providing them with local variables. To acquire the GPS coordinates of a particular location, the application will also start the GPS service. The data is then placed in an XML file along with the coordinates. The app then delivers this XML file to the base server for exhaustive analysis. The soil and weather data that would be generated from the sensor and the app would be stored in a database. The database's weather data comprises data on atmospheric temperature, precipitation, annual rainfall, wind speed, air pressure, and daylight hours. Information about soil comprises the kind of soil, the profundity of the sample, and the soil's temperature, humidity, and pH.

The application of the Internet of Things with cloud computing technologies such as AWS is a handful for the monitoring of any kind of soil parameters [19]. The interventions to address are intended to test the fundamental elements of soil, such as temperature and moisture content, which have a substantial impact on the soil's characteristics. Applications for speed synthesis can be quite helpful for both healthy people and people with challenges like dyslexia. Most sensors are mapped between 0 and 1023 quality. In this manner, the mapping of the moisture sensor is obtained for a different degree of moisture;

1) The soil is dry if the information reported is greater than 600 but less than 1000.
2) The soil is humid when the sensor reading is between 370 and 600.
3) The sensor is submerged in water if the sensor value is lower than 370.

To get the NPK estimations of the soil from the color sensor, soil samples need to be enhanced by adding nitrogen reagents, potassium reagents, and phosphorous reagents separately. The RMSE (Root Mean Square Error) number is calculated after applying a variety of classification techniques. To predict soil type, the method with the lowest RMSE value is chosen as the best one.

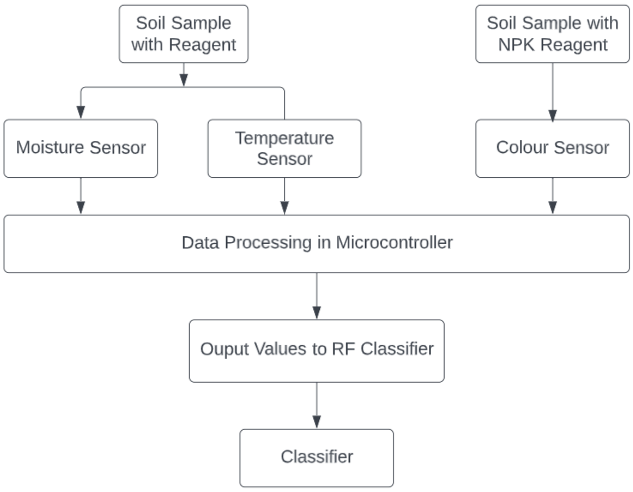

Fig. 7. Soil Analysis and Type Prediction Flowchart

Precision-Agriculture where the fields are managed by the zones divided according to the factors such as temperature, humidity, pH content, soil content, etc. There is an extensive range of MEMS devices that are used in precision agriculture [17]. The following devices are put forward in the paper:

1) Devices related to External environment factors:

<u>MEMS humidity sensor</u>: Most MEMS sensors are equipped with built-in electronic calibration systems and the digital ability to read values. These sensors are broadly classified into two major categories- resistive and capacitive. Resistive sensors are easy to fabricate and operate but lack stability. On the other hand, capacitive sensors provide long-term stability, a wide temperature range, low power consumption, and high precision; but are complex in operation.

Photosynthetically Active Radiation (PAR) Sensor: Photosynthesis is the process by which plants create their food. The process needs water, carbon dioxide, and most importantly sunlight in an appropriate visible range (470nm-700nm). This range is known as photosynthetically active radiation (PAR). PAR is the main factor for photosynthesis. PAR sensors contain photodiodes such as Silicon (Si), gallium arsenide phosphide (GaAsP), cadmium sulfide, etc. which are used to measure the light in the visible range and optical fiber.

Soil moisture and temperature Sensor: MEMS cantilever beams containing water-sensitive nano-polymer and on-chip MEMS piezo resistive temperature sensors are utilized to measure the values.

MEMS Solar Radiation Sensor: It detects PAR with a Febry-Perrot filter (Optical narrow passband filter) for the range 400nm-700nm.

2) Devices related to Soil content:

MEMS soil sensors: These devices measure the factors in the soil such as pH value, electrical and thermal conductivity, diffusivity, etc. For the measurement of pH value, an Ion-sensitive field effect transistor (ISFET) is used. It consists of an ion-sensitive electrode and a FET (Field Effect Transistors). A soil sensor based on poly (3,4-ethylene dioxythiophene) and polystyrene sulfonate (PEDOT-PSS) conductive polymer is designed to measure the moisture content of the soil.

3) Other devices:

MEMS-based Silicon microchannel devices combined with force-displacement sensors are used to monitor root growth and its contact with soil. MEMS microchip-based capillary electrophoresis sensor detects the presence of PR (Pathogenesis Related) proteins which is the indication of a pathogen attack. Devices such as Ecomatik Diameter Dendrometer small-DDS and Dynamax plant growth sensors are used to measure the dimensions of the fruit or stems from the branch using a linear variable, differential transformer (LVDT).

III. RESEARCH GAP

Only the presence of NPK nutrients is detected using a cantilever beam deviation in the study "Simulation of a Cantilever Beam Based Soil Nutrient Sensor" [15], however, the precise value of each nutrient cannot be determined with the aforementioned method.

Most research concentrates on traits. It is without a doubt required to assist in plant identification, classification, and prediction [8]. Applying ML approaches is feasible in the presence of a substantial dataset that connects inputs to output amounts [18].

In "NPK Soil Nutrients Identification for Corn using Optical Transducer with Mobile Application," a full hardware system called "NPKlyzer" that uses a photodiode sensor and a transducer to detect the NPK values in the soil has been developed [3]. It offers an entire hardware system. The architecture of the provided system is enormous and essentially stationary, making it challenging to move it about the field. The "Automation of Soil Nutrient Measuring System and Irrigation Control" [11] uses a similar optical transducer and offers a comprehensive system with a built-in fertilizer prediction system. This system has a problem in that it gives inaccurate measurements during transitions. According to the paper cited above, NPK nutrients were assessed in a cornfield [3], and NPK deficiency is measured in the maize fields.

The accuracy of the model reported in "Framework to identify NPK deficit in maize plants using CNN. Advances in Intelligent Systems and Computing" is not sufficient (80%) [7]. Additionally, it does not consider absolute values but only nutritional insufficiency.

The decision tree algorithm was able to forecast how much fertilizer the maize plant will receive with 93% accuracy [8]. The computerized picture analysis which is used to determine the percentage of ground cover can be deceiving. The area may also be covered by dead or damaged leaves; thus, it is also necessary to improve the image analysis method.

The values of NPK obtained in “Soil NPK Levels Characterization Using Near-Infrared and Artificial Neural Network” are obtained so with 99.8 percent accuracy with the help of NIR spectrography and ANN prediction modeling [10], but the data is not further processed to get more insights into the soil behavior thereby leaving us unrendered data for verification and usage. Similarly; even with the use of an Integrated Optical sensor, there is no method suggested for choosing the best crop type or fertilizer to improve crop quality [12].

In the study "Primary Nutrients Determination in the Soil Using UV Spectroscopy," the NPK levels of the soil are determined using chemical methods at any given time [9]. The conductivity of electrodes varies depending on the NPK content of the soil. For further electronic control systems to function, the change in conductivity must be transformed into electrical signals, which must then be processed further by a different system.

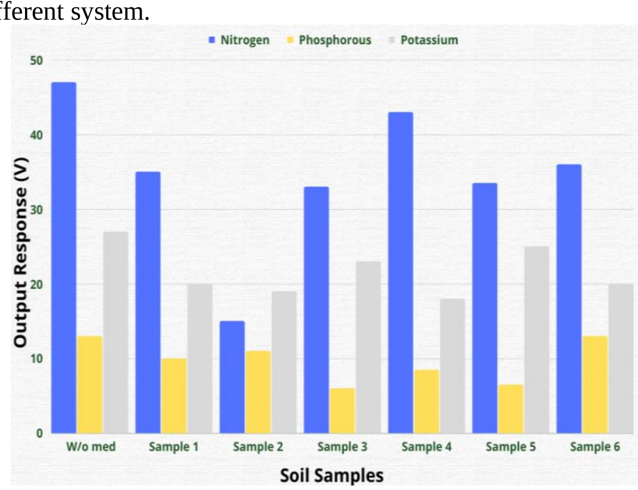

Fig. 8. Output Responses for NPK Samples

The suggested system employs preliminary assays that utilize the DUVA of both nitrates and nitrites. Although interferences from other chemicals in the water could arise and prevent an accurate nutritional assessment, nitrate levels should preferably be determined using their stronger band (about 200 nm), which enables a lower LOD and temperature-independent measurement. The suggested method has limitations brought on by electronic instrumentation, which could necessitate substantial financial inputs. Since interferences on the matrix would violate Bouguer-Lambert-Law, Beer's executing the quantification at the optimal intensity point for each scenario would only be valid in the absence of interferences. Therefore, every measurement must take into account how interferences affect the value obtained, and this may only be achievable when signal processing, chemometrics, and AI are combined [14].

Agrawal, R., Atray, M., & Sundari, S. K has mentioned a system in their paper, "Sensor Network Architecture for soil and weather data extraction and database generation." [1] that although the measurement of the external factors related to the soil like pH, temperature, precipitation, etc. is done with the addition of weather data abstraction; the values are just inserted into the XML file database. The further application of these values is not implemented in this paper.

Instead of directly detecting the NPK nutrient content of a soil sample, another IoT-based system described the procedures in "Soil Analysis and its Type Prediction with Speech Enabled Output using IoT and AWS." This system uses sensors and an ML algorithm to determine the soil's temperature and moisture content. When three different sensors are employed at different stages, the data collection process may take longer and require a larger setup [13]. The IoT model in [16] simply calculates the soil's nitrogen content.

IV. Conclusion

The proportion of NPK nutrients contained in the soil may be more easily and affordably determined thanks to this study, which benefits both farmers and academics. Extrapolated is responsible for upholding that only taking interference modes between all specimens into account makes it possible to precisely observe the levels of nitrogen, phosphorus, and potassium (NPK) in fertilizers employing UV-vis spectroscopy. Analytical-grade calibrations cannot be obtained when nitrogen is evaluated using bands and linear or logarithmic regression models. The creation of an analytical grade NPK monitoring system based on UV-vis spectroscopy and artificial intelligence will be evaluated in this carefully controlled experiment using micro-irrigation systems.

AI Technology, particularly Machine Learning algorithms and Deep Learning techniques, is employed in agricultural businesses, laying the groundwork for Industry 4.0. Specifically in digital image analysis and optical light-absorption models, ML methodologies in soil nutrient monitoring systems and crop prediction services have run into various disagreements. AI technology has advanced by integrating with computer-aided precision agriculture services to obtain potent data mining capabilities. There are still certain problems, for example, numerous neural network training parameters are altered, but there are no theoretical or practical frameworks to improve these models.

V. Future Scope

In the current study of MEMS sensors which use ion-selective electrodes to measure the concentration of the targeted nutrient, we can use a tunable laser that works in the visible region to detect all three NPK nutrients. This allows us to design a single structure to detect all three nutrients in the soil sample.

Another important point in the design of a MEMS sensor for the detection of nutrients in a soil sample is the small size of the sensor. It can be packaged in bulk inside other optoelectronic devices hence increasing the sensitivity. Also considering the importance of technology in the current era, it paves the way for the implementation of agriculture-related sensors in IoT devices. The Crop Management Device that has been presented, which uses algorithms created over this framework to assist farmers, is one systematic extension of this system. The size of the database might grow quite significantly with active engagement. As this work advances, we envisage improvisation in network architecture, soil sensors, and mobile applications. Non-invasive nutrient detection techniques can also be used such as spectroradiometers, reflectometers, and digital cameras to measure the NPK values.

Additionally, soil macronutrients like N, P, and K, a multitude of micronutrients notably copper, iron, manganese, molybdenum, and zinc are also essential for a crop's progressive growth, which affects the yield. By properly integrating these extra components and adhering to the right specifications, the system can be enhanced to measure these parameters.

The right framework that recommends the best fertilizers to address nutrient deficiencies can be used to identify the type of nutrient deficiency by utilizing supervised learning with a dataset that contains details about the type of nutrient deficiencies and related fertilizers. Both the crop and the soil datasets are used. The files include geographical and chemical characteristics of soil and crop features. The classification of soil series data and the prediction of appropriate crops can be done using algorithms like SVM and the Ensemble approach.

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