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Revolutionizing Farming: Iot-Enabled Organic Carbon Detection For Enhanced Agricultural Practices

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Abstract

The integration of the Internet of Things (IoT) has brought about transformative changes across diverse industries, and its application in agriculture, particularly in soil management, has become a focal point of research and innovation. This paper explores the paradigm shift enabled by IoT in detecting organic carbon in soil, with the overarching goal of advancing agricultural productivity and sustainability. Emphasizing the pivotal role of organic carbon in soil health, the research addresses the existing challenges associated with its detection and underscores the potential advantages offered by IoT-based solutions for precise and real-time monitoring. The study meticulously examines various IoT technologies, including sensors, data analytics, and wireless communication protocols, within the specific context of organic carbon detection. A thorough review of contemporary techniques, methodologies, and devices utilized in IoT-based organic carbon detection in soil is presented. The paper not only sheds light on the current state-of-the-art but also explores the advantages, limitations, and prospects inherent in the implementation of IoT-enabled systems in agriculture. The envisioned outcomes encompass enhanced soil management practices, heightened crop yields, and the simultaneous preservation of the environment. In essence, this research contributes to the expanding body of knowledge surrounding IoT applications in agriculture, specifically emphasizing the transformative potential of IoT-enabled organic carbon detection for revolutionizing farming practices and promoting sustainable agricultural development.

Keywords*: *IoT in Agriculture, Soil Management, Organic Carbon, Agricultural Productivity, Precision Agriculture, Real-time Monitoring, Soil Health, Data Analytics.

I. INTRODUCTION

Soil, frequently characterized as the cornerstone of agriculture, holds a crucial position in supporting life on Earth. The well-being and strength of soil exert a substantial influence on agricultural productivity, ecosystem stability, and worldwide food security. Grasping the intricate dynamics of soil constituents, with a special focus on organic carbon, stands as an essential requirement in contemporary agricultural methodologies.

1.1 Importance of Soil Health in Agriculture

The importance of soil health in agriculture is undeniable. Acting as a reservoir for crucial nutrients, water, and essential microbial life necessary for plant growth, soil plays a pivotal role. A thriving soil ecosystem supports vigorous crop development, guarantees nutrient accessibility, manages water retention, and alleviates environmental threats such as erosion and pollution. Consequently, the preservation of soil health is of utmost significance for sustainable agricultural practices and the continuity of global food production.

1.2 Role of Organic Carbon in Soil

Organic carbon, an integral constituent of soil organic matter, assumes a diverse role in soil fertility and ecosystem operation. Serving as a key energy source for soil microorganisms, it aids in nutrient cycling and promotes soil structure enhancement. Moreover, organic carbon plays a role in retaining moisture, consequently augmenting water accessibility for plant roots. Its existence cultivates a favourable environment for a variety of soil biota, promoting biodiversity and resilience within the soil ecosystem.

1.3 Need for Precise Organic Carbon Detection

Accurate detection and measurement of organic carbon content in soil are essential for several compelling reasons. Primarily, organic carbon serves as a pivotal indicator of soil fertility and overall quality. Monitoring its levels assists in evaluating soil health, providing valuable insights for effective crop production management. Secondly, a comprehensive understanding of variations in organic carbon content aids in the assessment of soil management practices, such as crop rotations and tillage, to maintain or improve soil organic matter levels. Additionally, precise detection of organic carbon content plays a crucial role in climate change mitigation by influencing carbon sequestration in the soil, contributing to the dynamics of global carbon cycling.

Given the critical roles and far-reaching implications associated with organic carbon, the demand for dependable and efficient methods for its detection and quantification becomes increasingly apparent. Accurate measurement techniques not only support enhanced agricultural management practices but also play a vital role in promoting sustainable land use and environmental stewardship.

II. IOT AND ITS APPLICATION IN AGRICULTURE

The Internet of Things (IoT) has surfaced as a ground-breaking technology with extensive applications in various industries, agriculture being a notable one. Within the agricultural sector, IoT assumes a crucial role in reshaping conventional farming methodologies, ushering in an era of data-driven precision, efficiency, and sustainability. The following provides an overview of IoT and its noteworthy applications within the realm of agriculture.

2.1 Applications of IoT in Agriculture

A. Precision Farming

The implementation of the Internet of Things (IoT) in agriculture facilitates precision farming through the deployment of sensors for data collection on soil moisture, temperature, humidity, and nutrient levels. The gathered data is then analyzed to support informed decision-making regarding irrigation, fertilization, and pest management. Precision agriculture optimizes the allocation of resources, reduces inefficiencies, and improves both crop productivity and quality.

B. Smart Irrigation Systems

Intelligent irrigation systems empowered by IoT utilize sensors and weather forecasts to deliver precise amounts of water to crops based on their individual needs. These technologies enhance water efficiency, minimize water wastage, and prevent both overwatering and underwatering.

C. Crop Monitoring and Management

IoT devices, including drones and satellite imagery, play a pivotal role in crop health monitoring, disease detection, and plant stress assessment. This technological capability empowers farmers to identify potential issues in their fields early on, facilitating timely interventions and mitigating crop losses.

III. LITERATURE REVIEW

The literature review comprehensively explores a diverse array of studies focused on leveraging Machine Learning (ML) and various modeling techniques to address intricate challenges in soil analysis, crop yield prediction, and precision agriculture. Researchers across different domains employ ML models to extract meaningful insights from soil-related data, optimize crop management practices, and enhance decision-making processes in agriculture.

In a study by Patil and Umarji [1], Convolutional Neural Network (CNN) architectures are utilized for crop disease identification, providing valuable support to farmers engaged in organic agricultural crop protection. Gholap et al. [2] and Gudavalli et al. [3] explore classification and clustering approaches using algorithms such as J48, Naïve Bayes, and various clustering techniques, analysing attributes and parameters for soil classification and enhancement of clustering methods, respectively. Ashwini et al. [4] propose a methodology employing digital image processing and pattern recognition models for soil sample grading and classification based on diverse scientific features and parameters.

The forecast of soil organic carbon relies on an impartial linear predictor.[5]. Researchers are dedicated to the prediction of soil fertility, organic carbon content, and diverse soil nutrients, employing models like the Boosted Regression Tree. An application of the Boosted Regression Tree model includes its utilization in the analysis of Sicilian soil, aiming to predict the presence of organic carbon [6]. In the soil of eastern Australia, the anticipation of organic carbon presence is conducted through the utilization of a genetic algorithm-based feature selection technique coupled with a random forest algorithm [7]. The prediction of different soil types from mid-infrared spectra of Cation Exchange Capacity (CEC) and soil acidity (pH) in the presence of organic carbon is accomplished through the application of the Partial Least Squares technique [8]. The assessment of soil fertility is conducted through the application of Bayesian network methodology, considering factors such as the presence of zinc, organic carbon, phosphorous, potassium, iron, copper, nitrogen, and other soil nutrients, along with the soil pH value [9]. The analysis and assessment of wind speed formation for geographic portability are conducted through machine learning algorithms. Climate and soil parameters, crucial for crop growth and precision farming, undergo effective analysis using models such as Artificial Neural Networks (ANN), Bayesian networks, Support Vector Machines (SVM), Random Forest (RF), and Decision Trees (DT) [10].
In the article 'Remote Sensing Techniques for Soil Organic Carbon Estimation: A Review' authored by Theodora Angelopoulou et al. in 2019, the exploration revolves around the utilization of Visible-Near Infrared–Shortwave Infrared (VNIR–SWIR) remote sensing techniques spanning the wavelength range of 400–2500 nm for estimating soil organic carbon. The comprehensive review delves into the methodology, findings, and introduces the concept of soil spectroscopy. It meticulously addresses challenges encountered in the process, including atmospheric corrections, vegetation cover, and soil moisture. The discussion encompasses an unbiased analysis of both the advantages and disadvantages of these approaches, concluding with insights into future considerations.

IV. RESEARCH METHODOLOGY

Detection of organic carbon in soil encompasses various methodologies, each offering unique advantages based on specific requirements. The following methods are commonly employed:

A. Walkley-Black Method:
This method involves oxidizing organic carbon using a mixture of dichromate and sulfuric acid.
The oxidized carbon is titrated with ferrous ammonium sulphate.

B. Titration Methods:
Direct titration methods entail titrating soil extract with a standardized solution.
Indirect titration methods involve oxidizing organic carbon to release CO2, which is then titrated.

C. Combustion Methods:
Soil samples are burned in a furnace to convert organic carbon to CO2.
The released CO2 is measured using infrared analysers or titrated with a known reagent.

D. Infrared Spectroscopy:
This method utilizes the absorption of infrared radiation by organic carbon.
The amount of absorbed radiation is proportional to the organic carbon content.

E. Loss-on-Ignition (LOI):
Involves weighing soil before and after ignition at a high temperature.
The loss in weight represents the organic carbon content.

F. Chromatographic Methods:
Gas chromatography and liquid chromatography can separate and quantify organic compounds in soil.

G. Spectrophotometric Methods:
UV-Vis spectrophotometry measures color changes in reaction with reagents like dichromate.

When selecting a method within the research methodology, it is essential to consider factors such as sensitivity, cost, and sample size based on specific needs. Each method presents a distinct approach to organic carbon detection, providing flexibility for researchers to choose the most suitable technique for their study.

Importance of Soil pH
Soil pH serves as a measure of the soil's acidity or alkalinity, reflecting its hydrogen ion concentration and playing a crucial role in soil health and plant growth. The pH scale, ranging from 0 to 14, designates values below 7 as acidic, 7 as neutral, and values above 7 as alkaline (basic). In humid tropical regions, heightened soil acidity is a common occurrence, attributable to various factors:

A. Loss of Basic Cations:
Basic cations (positively charged ions like calcium, magnesium, and potassium) are vital for neutralizing soil acidity. Excessive rainfall and leaching processes in these regions can lead to the loss of these cations, thereby elevating soil acidity.

B. Intense Leaching Conditions:
Tropical areas with high rainfall experience intense leaching, where water carries away nutrients and basic ions from the soil, exacerbating soil acidity.

C. Fertilizer Use without Lime:
The application of nitrogen-based fertilizers without sufficient lime contributes to soil acidification. Over time, nitrogen fertilizers can increase soil acidity, particularly when there's an imbalance with other nutrients.

D. Alkaline pH (above 7.0):
Alkaline pH levels may limit the availability of micronutrients such as iron, zinc, and copper, rendering them less accessible to plants.

4.1 Classification of Soil
The interplay between soil pH and microbial nutrient availability is of significance. pH influences microbial activity, and fluctuations in pH levels can impact the composition and functionality of microbial communities. Understanding these dynamics is essential for effective soil management and sustainable agricultural practices.

TABLE I SOIL PH

Rating	**Soil pH Range**
Very strongly alkaline	> 10
Strongly alkaline	9.1 - 10
Moderately alkaline	8.1 - 9
Slightly alkaline	7.1 - 8
Neutral	7
Slightly acidic	6.5 - 6.9
Moderately acidic	5.5 - 6.4
Highly acidic	4.5 - 5.4
Strongly acidic	< 4.5

Utilizing IoT-based smart farming coupled with an Extreme Learning Method (ELM) classifier is a strategic approach designed to streamline data collection, transmission, and analysis, with the ultimate goal of improving the efficiency and accuracy in predicting soil characteristics crucial for agricultural productivity. The process commences with the collection of soil samples facilitated by IoT-based smart farming technologies, ensuring swift and seamless data transfer between farms and farmers, thereby facilitating rapid access to essential soil information.

At the heart of this methodology is the implementation of the Extreme Learning Method (ELM) classifier. Through meticulous training with designated parameters, the ELM classifier identifies the optimal configuration that maximizes predictive accuracy. Fine-tuning the model involves parameter selection, where various combinations are tested to optimize micronutrient identification and pH classification. For pH classification, the classifier designates a value of 150 to the hidden neuron parameter and explores a range of values (between 10 and 200) for further calibration.

These operations contribute to enhancing the model's effectiveness and guaranteeing the precision of soil parameter predictions. In its entirety, this sophisticated approach combines cutting-edge technologies, thorough cross-validation, and adaptive model optimization to quickly and accurately categorize soil parameters. Through the utilization of IoT-enabled data collection and the rapid learning capabilities inherent in the ELM classifier, this methodology is positioned to transform soil analysis, providing farmers with timely and accurate insights for well-informed decision-making in agriculture.

4.2. Block and circuit diagram of how Organic carbon detection is possible with IoT

A Systematic working view of IoT-enabled Organic Carbon Detection System (Abhiram et al., 2022), as shown in Fig. 1.

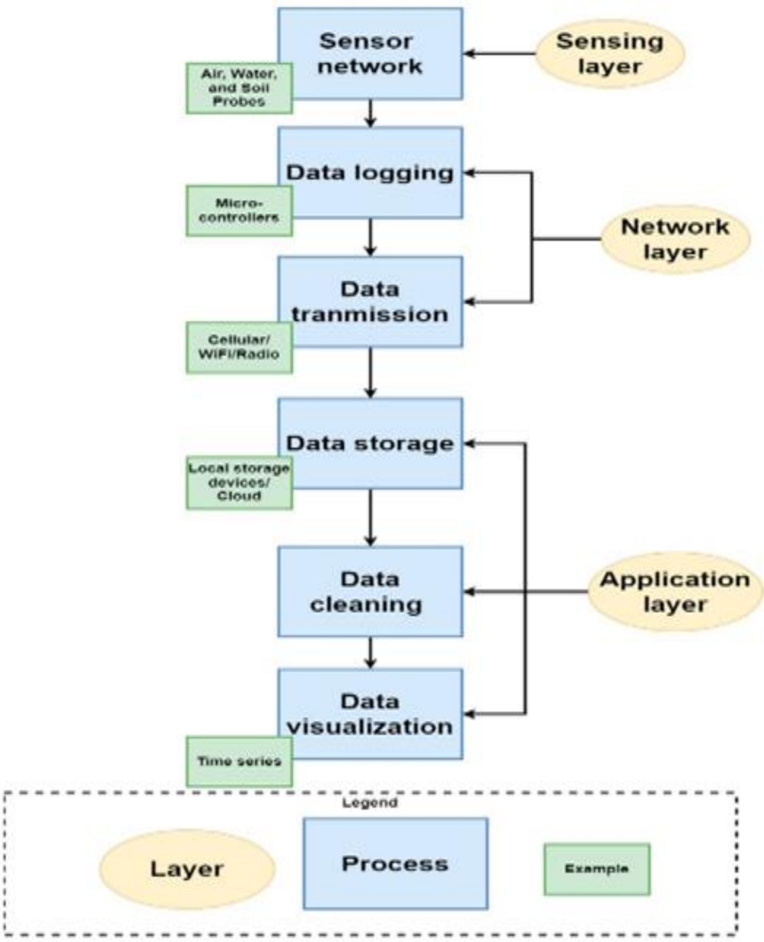

Fig. 1 A Systematic working view of IoT enabled Organic Carbon Detection System (Abhiram et al., 2022)

Fig. 2 shows IoT-enabled Organic Carbon Detection System algorithm flow chart

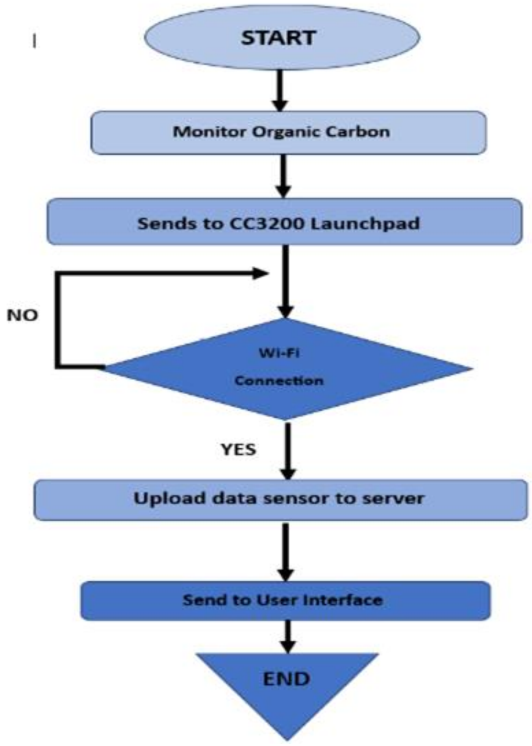

Fig. 2 IoT-enabled Organic Carbon Detection System algorithm flow chart

In the process of detecting organic carbon, specialized soil sensors are strategically placed in agricultural fields to capture real-time data. This data is transmitted wirelessly to an IoT gateway, facilitating smooth communication. Subsequently, cloud platforms process and analyse the organic carbon data through algorithms, providing users with access to valuable insights through a user-friendly interface. This empowers farmers and researchers to make informed decisions and optimize agricultural practices.

V. CONCLUSIONS

The analysis of soil samples provides factual insights into their nutrient composition and overall characteristics. A notable proportion of soil samples exhibits deficiencies in essential elements while showing satisfactory levels in others. Specifically, Sulphur content in the soils is observed to be deficient, measuring below 10 ppm, indicating a potential need for Sulphur supplementation to facilitate optimal plant growth and development. Conversely, potassium levels are moderately high, ranging between 245-295 kg K2O/ha, suggesting an ample presence of potassium in the soil, potentially reducing the need for additional potassium-based fertilizers. Micronutrient composition in the soil samples, as shown in Table II.

TABLE III MICRONUTRIENT COMPOSITION IN THE SOIL SAMPLES

Parameters	Sample 1	Sample 2	Sample 3	Sample 4
Cu (ppm)	1.32	1.35	1.12	1.42
Mn (ppm)	2.08	6.82	2.2	8.7
Fe (ppm)	2.34	2.96	2.64	3.46
B (ppm)	0.35	0.19	0.46	0.35
Zn (ppm)	0.45	0.36	0.0	0.7
S (ppm)	10.12	18.65	38.05	46.72
K (kg/ha)	275.82	294	267	397
P (kg/ha)	32.6	38	14	17.84
N (kg/ha)	521	382	394	798
OC (%)	0.5	0.42	0.38	1.6
EC (millimhos/cm)	0.18	0.09	0.082	0.2
pH	8.2	8.3	8.04	8.4

Optimizing Neural Network Performance: Cross-validation Accuracy (%) vs. Number of Hidden Neurons for Soil pH Identification is shown in Fig. 3.

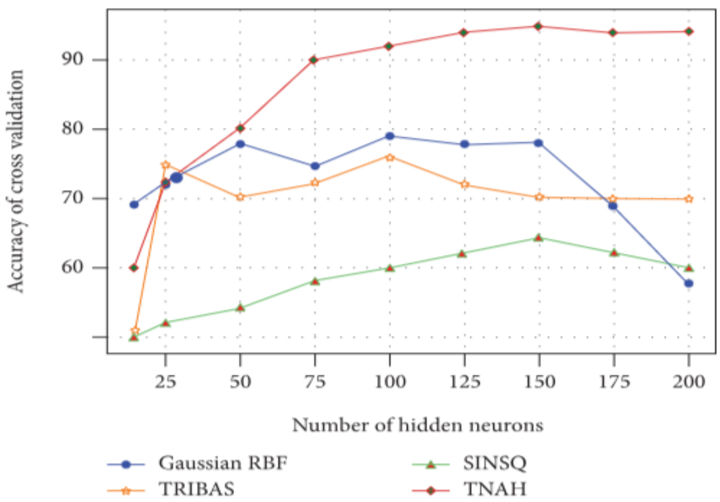

Fig. 3 Optimizing Neural Network Performance: Cross-validation Accuracy (%) vs. Number of Hidden Neurons for Soil pH Identification

Phosphorus content falls within a medium range, spanning from 20-53 kg P2O5/ha. Although not significantly deficient, these levels might benefit from moderate supplementation to enhance soil fertility and promote improved crop growth. Nitrogen content, rated as moderately high, ranges between 250-550 kg/ha, indicating sufficient nitrogen levels available for plant uptake, thereby supporting crop development.

Concerning organic carbon, the soil exhibits medium levels (> 0.5%), signifying a moderate presence of organic matter that contributes to soil health and fertility. Additionally, the soil displays an alkaline reaction, with a pH measurement exceeding 8.2. This alkaline nature might impact nutrient availability and plant growth, especially for acid-sensitive plants.

DTPA is Diethylenetriaminepentaacetic acid. DTPA is a chelating agent commonly used in soil and environmental chemistry to extract and measure the availability of certain micronutrients, particularly copper, iron, manganese, zinc, and other metals, from soil samples. Micronutrients extracted using the DTPA method reveal satisfactory levels of Copper (Cu) and Iron (Fe), indicating their sufficient presence. However, deficiencies are observed in Manganese (Mn), Boron (B), and Zinc (Zn), suggesting potential requirements for supplementation to address these deficiencies and optimize soil nutrient balance for healthy crop growth.

Thus, while the soil exhibits adequate levels of certain nutrients such as potassium, nitrogen, and organic carbon, deficiencies in Sulphur, Phosphorus, and specific micronutrients necessitate targeted interventions and fertilization strategies. This factual understanding of soil composition is crucial for evidence-based agricultural practices, enabling farmers to implement precise and tailored soil management techniques to maximize crop productivity and overall soil health.

In the domain of IoT-enabled organic carbon detection in soil, the integration of real-time data acquisition and mobile technology offers farmers a practical means to access essential information from a distance. In this operational framework, soil sensors gather accurate organic carbon data, which is wirelessly transmitted to an IoT platform and swiftly delivered to farmers' mobile devices. This robust system provides farmers with prompt updates on soil conditions, empowering them with real-time insights to make informed decisions and optimize agricultural practices, regardless of their location.

In conclusion, the integration of Internet of Things (IoT) technology in agriculture stands as a transformative force, ushering in a new era in traditional farming practices. This shift has unleashed substantial advancements, fostering data-driven precision, efficiency, and sustainability across various aspects of agricultural operations. The diverse applications of IoT in agriculture, ranging from precision farming to smart irrigation, crop monitoring, livestock management, and supply chain optimization, have yielded tangible benefits. Real-time access to data on soil conditions, crop health, weather patterns, and livestock behavior empowers farmers to make informed decisions, optimize resource utilization, and adeptly manage risks. The overarching advantages brought about by IoT in agriculture include heightened productivity, resource efficiency, cost reduction, and improved decision-making. Leveraging IoT-driven insights enables farmers to achieve increased crop yields, enhanced crop quality, and minimized resource wastage, ultimately leading to elevated profitability and sustainability.

Looking forward, the future of IoT in agriculture holds significant promise. Continuous advancements in IoT technologies, coupled with the integration of artificial intelligence, machine learning, and big data analytics, are anticipated to further refine predictive capabilities and automate farming practices. This evolution is poised to revolutionize the agricultural sector, ensuring food security, mitigating environmental impact, and effectively addressing challenges posed by climate change and global population growth. In essence, the adoption and integration of IoT in agriculture represent a pivotal juncture in modern farming, endowing farmers with sophisticated tools and insights to navigate the complexities of agricultural production. The ongoing innovation and implementation of IoT technologies are indispensable for constructing resilient, sustainable, and efficient agricultural systems for the future.

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