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Soil Sensors as a Service: Low-Cost Soil Diagnostics System using IoT

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Abstract: To ensure healthier crop yields in agriculture, proper management of the existing soil nutrients is crucial. The continuous cultivation of plants negatively impacts soil fertility, causing its decline. Farmers face the time-consuming task of visiting laboratories to test soil fertility. However, a novel optical transducer has been developed for detecting and measuring the presence of Nitrogen (N), Phosphorus (P), and Potassium (K) in the soil. This transducer plays a vital role in determining the appropriate amount of these nutrients to enhance soil fertility, thereby improving soil quality and reducing the unnecessary use of fertilizers. By analyzing the absorption of light for each nutrient, the N, P, and K values of soil samples can be determined. Technological advancements, particularly in the field of agriculture, have paved the way for progress. The proposed framework employs Internet of Things (IoT) technology to identify soil nutrients. Sensors are utilized to measure pH, temperature, moisture, and NPK levels. This data helps farmers assess soil fertility levels before sowing, enabling them to apply the required amount of fertilizers accurately. Consequently, this approach facilitates higher crop yields. IoT, an extensive domain focusing on gathering information through the internet anytime and anywhere, is instrumental in monitoring systems in the absence of human intervention. It employs sensors that prove beneficial even in agricultural applications, enabling farmers to experiment with soil and maintain its fertility.

Keywords: NPK sensors, Artificial Intelligence (AI), Long short-term memory (LSTM), Fusion of sensors, Intelligent Devices, Software-based Sensors, Wireless Sensor Networks (WSNs).

I. INTRODUCTION

Technological advancements in the past decade have facilitated the accessibility of predictive modeling processes across various fields. The widespread adoption of artificial neural networks (ANNs) and deep learning (DL) algorithms has increased the autonomy of computers in tasks such as classifications, regressions, and predictions. This progress holds significant importance within the industry 4.0 paradigm, where these advanced analysis tools are integrated into smart metering systems based on Internet of Things (IoT) architectures. The latest developments in artificial intelligence (AI) enable the analysis of large datasets generated by intelligent sensor nodes, extracting valuable insights to optimize industrial processes. The agricultural industry, in particular, is increasingly interested in leveraging AI-based optimization of IoT architectures.

Precision farming, also known as smart farming, utilizes technologies such as smart meters, wireless sensor networks (WSNs), unmanned aerial vehicles (UAVs), and smart camera nodes to achieve various goals. These goals include reducing pesticide usage for sustainable and eco-friendly production, optimizing irrigation to minimize water waste, improving overall farm resource management, diagnosing and preventing plant diseases to enhance harvest outcomes, and reducing farming costs.

A. Problem Background

Smart farming plays a crucial role in combating climate change, as efficient utilization of natural resources is essential in mitigating its impact. Agriculture focuses on enhancing monitoring efficiency by integrating DL algorithms as decision-support tools in agricultural activities. DL algorithms have been employed to analyze environmental factors affecting crop yield and irrigation scheduling. Convolutional neural networks (CNNs) and long short-term memory (LSTM) networks have been utilized to study the factors influencing irrigation scheduling. Moreover, LSTM-based neural networks have been proposed for smart irrigation systems.

Disease detection is another important area of study that can greatly benefit from AI integration. Various approaches, such as shallow visual geometric groups (VGG), deep residual neural networks, LSTM, transfer learning, and embedded systems with recurrent neural networks (RNN), have been employed for plant disease identification and classification. Soft sensors, which are virtual sensors capable of performing multiple measurement tasks and processing data, have gained significance in this field. ANNs have enabled the development of advanced soft sensors that can identify previously unpredictable correlations between measurements.

Soft sensors are particularly useful when physical sensor installation is impractical or sensor failure can cause significant damage. Their implementation has been explored in instrument fault accommodation and timber bundle volume measurement in the Swedish forest industry. In the domain of precision agriculture, DL algorithms have been evaluated for their applicability in the soft sensor concept. One study focused on estimating the cost of sensors required for accurate irrigation programming in cultivated fields. The analysis highlighted the importance and costliness of soil moisture sensors in weather stations used for agricultural purposes.

B. Literature Review

Soil moisture estimation has been approached using WSNs and satellite imagery, but these methods can be expensive and have limited accuracy. Researchers have explored leveraging above and below-ground sensors to reduce costs and improve analysis and prediction accuracy. Some studies have attempted to predict soil moisture by combining standard environmental sensors such as ambient temperature and humidity sensors with soil moisture sensors. These studies have implemented smart sensor nodes connected to cloud platforms using protocols like Message Queue Telemetry Transport (MQTT). However, these approaches face challenges such as the high cost of soil moisture sensors and the need for multiple sensors to improve accuracy over large areas of land. Sensor failures and measurement errors due to harsh environmental conditions and improper installation also pose limitations.

Other approaches involve the use of support vector machines (SVM), digital photography, machine learning methods, graph neural networks, intelligent multi-output regression models, DL regression networks, and other techniques for soil moisture prediction. To adhere to the soft sensor concept, collected data needs to be supplemented with an estimation and prediction algorithm based on exogenous variables related to the target variable. However, in many cases, the correlations between environmental variables are weak, limiting the applicability of classical estimation and prediction algorithms such as Kalman filtering and Fuzzy logic.

II. PROPOSED SYSTEM

A soil diagnostic sensor, utilizing planar ion selective electrodes, is employed to detect the N, P, K, and pH contents in soil samples. By measuring environmental conditions that impact crop production and monitoring indicators of livestock health, IoT technology in agriculture facilitates efficiencies that reduce environmental impact, maximize yield, and minimize expenses.

LoRa Technology, known for its long-range and low-power wireless capabilities, enables the utilization of cost-effective sensors to transmit farm data to the Cloud. This data can then be analyzed to enhance operational processes. Receive crop and soil alerts only when desired and relevant to your specific crop. AI and ML techniques are implemented for crop yield recommendations.

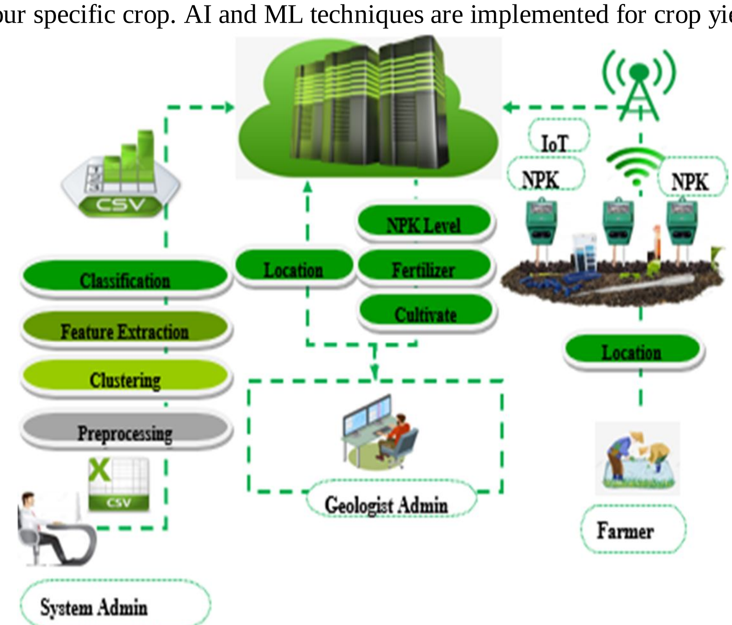

FIG: Architecture Diagram

The proposed IoT infrastructure for smart farming technologies is characterized by a WSN based on a self-organized and self-configured mesh topology. This topology enables the collection of data from a distributed network of sensor nodes deployed across a wide field.

The sensor nodes operate independently and are self-powered, gathering various environmental data and transmitting it to a central gateway (referred to as the root node or access point).

The sensor node proposed in this system is a cost-effective and energy-efficient device comprising several subunits:

1) The power supply unit utilizes a photovoltaic (PV) panel to recharge two lithium-ion batteries via a customized dc-dc converter.
2) The acquisition and elaboration unit employs the ESP32 system-on-a-chip microcontroller to acquire data from analog and digital sensors. The acquired data is then transmitted to the central gateway using the IEEE 802.11 Wi-Fi protocol. Digital sensors are directly managed by the microcontroller, while analog sensors are acquired through suitable conditioning circuits and two embedded eight-channel 12-bit successive approximation register (SAR) analog-to-digital converters (ADC).
3) An external 3D Bi antenna.
4) A sensor pack consisting of various transducers.

The proposed WSN has been deployed in an olive grove near Pisa, Tuscany, central Italy. Ten battery-powered sensor nodes were strategically placed in different locations within the olive grove, collecting environmental and soil parameters for over a year.

III. DATA ANALYSIS AND NETWORK TRAINING

Upon completing the data collection, a thorough analysis was conducted to identify any errors and explore correlations that could enhance the estimation of soil relative humidity. The collected data includes the timestamp, ambient temperature (At), relative air humidity (RHa), soil temperature (St), relative humidity of the soil (VWC), light radiation (Rad), and operational status values of the intelligent sensor.

A correlation matrix was generated, showing stronger correlations of air temperature, relative air humidity, and soil temperature with other features. On the other hand, light radiation and relative humidity of the soil had weaker correlations. To improve soil moisture prediction, additional data on rainfall was included, obtained from the hydrological and geological service of the Tuscany Region, Italy, despite the absence of an installed rainfall sensor.

The inability to perform linear regression due to insufficient correlations between features led to the adoption of a regression method using a specific machine learning algorithm. Decision tree learning in the form of a multivariate regression tree was utilized for comparison with the proposed DL algorithm. This algorithm is commonly used in data mining, machine learning, and statistical applications for classification, decision-making, and prediction tasks.

The performance of the LSTM network was evaluated through tests on various hyperparameters, including the sequence length for warmup, sampling rate, batch size, number of epochs, learning rate, and data split for training and validation.

The network architecture was designed accordingly, with an input layer accommodating the input variables (St, RHa, Gt, Rad, and Rain), an LSTM layer with 32 units, and an output layer with one neuron for regression. The training utilized the mean square error loss parameter and the Adam optimizer.

IV. RESULTS AND DISCUSSION

After training the neural network, the results were evaluated using three sets of measurements taken at different locations over at least nine months. The data variability was high, encompassing changes in temperature, rainfall, and seasons. The performance of the neural network was compared with a benchmark algorithm, namely the regression tree, using the measured values versus the predicted values. The RMSE (Root Mean Square Error) was calculated for both the neural network and the regression tree.

The analysis of the SOE function showed that the first dataset had the lowest error, with the average relative error within 5% for most observation windows. The second and third datasets exhibited larger mean relative errors, but the probability of exceeding 0.08 remained below 10%.

In summary, the analysis confirmed the improved performance of the LSTM network for soft sensing compared to traditional machine learning algorithms, particularly the regression tree and NARX.

V. CONCLUSION

The Objective of this research is to enhance the performance of a WSN (Wireless Sensor Network) used in smart farming by introducing a soft sensing solution. The WSN comprises ten autonomous sensor nodes that are equipped with sensors for measuring air temperature and humidity, soil temperature, soil moisture, and radiation. To overcome the limitations associated with physical sensors used for soil relative humidity measurement, a DL-based soft sensing algorithm is proposed to implement a virtual soil moisture sensor.

To enhance the accuracy of crop and fertilizer prediction in our monsoon climate, we propose combining the hardware infrastructure with Azure notebooks. Furthermore, efforts are being made to reduce the size of the sensors, making them more compact. Substantial improvements are being implemented to expand the dataset size. These enhancements not only lead to improved crop maturity and quality but also increase resilience against diseases and pests while promoting overall growth. Conducting soil testing before each crop season remains the most reliable method for determining the specific fertilizer requirements.

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