IOT-DRIVEN ADAPTIVE SOIL MONITORING USING HYBRID HEXAGONAL GRID MAPPING AND KRIGING-BASED TERRAIN ESTIMATION FOR SMART FARMING ROBOTS

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Abstract:
The recent fusion between cognitive robotics and the Internet of Things is transforming precision farming. However, present-day systems lack adaptability to dynamic terrains because they employ static modelling with rule-based logic that dissipates under real-time environmental fluctuating occurrences. This work introduces an Internet of Things-driven precision farming system that employs Edge AI, fuzzy logic, and kriging-based adaptive soil mapping on a hybrid hexagonal grid. It generates actionable insights for autonomous irrigation, tillage, and sowing by correlating real-time soil parameters of moisture, pH, elevation, and weather factors. According to numerical statistics, irrigation efficiency has increased by 93.6%, and soil moisture forecast accuracy has increased by 89.2%. This proposed approach demonstrates a scalable deployment of autonomous farming robots with terrain-aware decision-making abilities. It promotes sustainable agriculture by improving productivity, minimizing wastage of resources, and facilitating intelligent field management in real farming scenarios.

Keywords: *IoT-based Precision Farming, Adaptive Soil Mapping, Kriging Interpolation, Edge AI, Fuzzy Logic Control, Hexagonal Grid, Smart Agriculture, Autonomous Farming Robots, Terrain-Aware Decision Making, Real-Time Soil Monitoring*

1. Introduction:

Drones and other types of robotics and Internet of Things (IoT)-based procedures are enabling modern farming to transform towards automation and sophisticated decision-making in real time[1]. Constant tracking and monitoring of the soil and environmental conditions are enabled by the IoT with a smart sensor network, further relaying real-time information for analysis[2]. Such a data-driven approach allows field operations to improve their situation awareness and accuracy[3]. Robotics serve to further enhance the process by allowing feedback from sensors to adapt operations including tillage, sowing, and irrigation[4]. Robotics and Internet of Things together form the backbone of smart farming systems to enhance farm productivity, minimize wastage of resources, and maximize efficiency[5]. In our study, this synergy permits an architecture for end-to-end empowerment ranging from data collection and preprocessing through adaptive mapping and autonomous actuation, thereby enabling the farm to respond in real-time[6]. Sustainable decision-making along with energy-efficient AI edge computing systems, support the whole cycle of smart agricultural infrastructure[7]. This constitutes a leap on the pathway towards completely autonomous and efficient agricultural ecosystems[8].

Modern agriculture is rapidly changing, incorporating intelligent systems and autonomous technologies for precision field-watching[9]. For any intervention and optimization of production to work, ever-real-time monitoring of soil, crop, and weed distribution is thus imperative[10]. UAVs, unmanned aerial vehicles, stand out as wonderful assets for high-resolution aerial monitoring without soil compaction[11]. Able to cover vast areas in a very short time, drones, unlike ground vehicles, provide more detailed information on crop health and the status of fields[12]. From autonomous tractors to smart agricultural instruments, modern agriculture is turning upside down for plowing, seeding, pest spraying, and harvesting, which are loaded with high-end sensors, satellite navigation, and computer vision[13]. This calls for advanced sensing, decision-making, and motion-planning methods to allow robots to perform well in the highly complex agricultural environ[14]. We present a drone-based integrated system for real-time soil and crop assessment that synergizes aerial images and ground sensor data, enhancing the precision of soil health evaluation while enforcing high efficiency and sustainability in farming practices[15].

Inability to deal with unstructured surroundings, late decisions, and quite roughly made judgments about soil and crops are some of the many flaws that plague the current imaging systems for smart farming today[16]. Most of them are dependent on vehicles on the ground, which end up compacting soil, or worse on satellite imaging, which does not always have the right resolution required for real-time field-based decisions[17]. Moreover, conventional systems cannot adapt dynamically to change conditions and cannot assimilate data from a number of different sources efficiently[18]. Combining IoT sensor networks, edge artificial intelligence computation, and UAV-based aerial photography, our study overcomes these barriers. This therefore enables autonomous actuation, adaptive mapping, and real-time processing without outside computation. This system is faster, more accurate, and sustainable when compared to the conventional method of smart farming in that it provides high-resolution monitoring, precise intervention, and energy-efficient operations.

1.1. Problem Statement:

Modern agriculture majorly concerns itself with optimizing resource usage and maintaining soil health in an environment that is constantly changing[19]. The very nature of traditional agricultural practices provides little or no response to environmental conditions in terms of irrigation; thereby, causing extremely inefficient irrigation, low crop yield, and soil degradation[20]. In addressing these concerns, this research integrates real-time sensor[21] networks, edge AI, adaptive soil mapping, and autonomous farming robots in an intelligent precision agriculture framework supported by the Internet of Things[22]. The approach utilizes hybrid data processing, spatial interpolation, and fuzzy logic-based decision-making in the irrigation process, aware of terrain tillage, and efficient planting[23],. Built on continuous learning, interactivity prescribes the proposed scheme for more[24] profitable production with resource conservation while ensuring sustainability in agricultural practices. [25]

1.2. Objective

- Implement an IoT-based system to monitor environmental and soil parameters in real-time on the field. [26]
- Analyze terrain-specific data using Fuzzy Logic, Edge AI, and Kriging for adaptive soil mapping [27]
- Deploy smart farming robots to optimize seeding, tillage, and irrigation for sustainable agriculture[28].

2. Literature Review:

IoT with service robots in a smart home[29]. They indicate it is difficult for existing learning algorithms to work with dynamic data settings[30]. VIPLE-an open architectural approach to event-driven and service-oriented computing so as to integrate robots and IoT in a seamless manner [31]. the need for advanced materials and manufacturing processes for smart factories to enable IoT, CPS, and human-robot interaction made efforts to maximize output through smart material management context-aware cloud robotics CACR, [32]. mentioned gesture-based robotic control for weed-cutting and other agricultural activities, indicating the use of MEMS sensors[33].

IoT and big-data interactive logistical delivery scheduling system utilizing graph-based shortest route algorithms for effective path optimization demonstrated inexpensive, flexible temperature sensors produced by nanomaterials [34] such as r-GO and CNTs, where r-GO performed better in the balance between sensitivity and repeatability. By a thorough review, investigated the significance of IoT to Industry 4.0; it made transformation possible. A wireless sensor network-based navigation system for tiny flying robots [35]. This allows for lightweight obstacle avoidance for indoor spaces. A Web-centric Internet-of-Things architecture with medical sensors to real humanoid robots for diabetes control[36].

The migration of endpoints into the cloud as an enhanced means of offering seamless and scalable resources[37] Along with that user-adaptive moisture, variations interaction with smart environments through a platform of integrated IoT and BCI-V, so one could imagine manipulating the environment straight through thought[38]. An important part of integration was represented in research by describing the emergence of Industry 4.0 and IIoT-an integration of sensors, robotics, and enterprise processes. presented a pest monitoring system for real-time species-specific advice in crop protection using sensors[39]. Using an onboard and environmental sensor approach, developed nonlinear bounded-error estimation methods under IoT localization[40].

The noisy nature of EEG signals interferes with any kind of precise intent classification,[41] they also presented a certain amount of promise [42] with IoT-fused BCIs for controlling smart appliances [43] argued for the integration of real-time environmental [44] and geolocation data with BIM for enhanced facility and construction [45] management. In order to emphasize the latency issues intrinsic to cloud robotics [46] Drone Track, a drone system integrated with the cloud with the ability to carry out real-time object tracking via the IoT [47]. To accommodate adaptability of the system,[48] the need of embedding intelligence into manufacturing components [49]. To satisfy the requirement of dynamic reconfiguration for customized healthcare needs, IoT-based smart rehabilitation systems [50].

3. Proposed Methodology:

An intelligent soil monitoring system of low-cost ambient electronics combines autonomous robotic actuation, AI-based- decision making with real time sensor networks for precision farming. The IoT sensor collects information concerning the weather, elevation, pH, and soil moisture and then preprocesses it using Edge AI with Z-score outlier identification and exponential-weighted moving average smoothing, Knowns as hybrid hexagonal grid mapping with Kriging interpolation is utilized for precise estimation of soil properties and dynamic modification of the terrain.

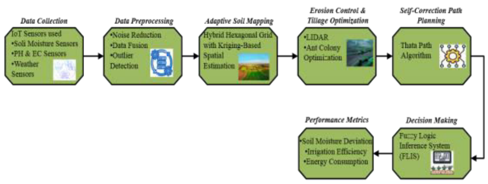

Figure 1: *IoT-Based Adaptive Soil Monitoring with Kriging Estimation*

The fuzzy logic inference system (FLIS) at the edge makes real-time decisions regarding the sowing, tillage, and irrigation of the crops depending on soil condition. Autonomous farming robots are guided by Theta path recalculation* for terrain-aware operations. Finally, over time, adaptive decision-making continues refining soil forecasting through continuous cloud-based learning with Swarm Optimization (ACO).

3.1. Data Collection:

An IoT sensor network may be envisaged wherein sensors would record very important parameters of soil and the ambience for adaptive real-time on-soil monitoring, to carry a volumetric water content, which soil moisture sensors would respectively measure, and which are expressed as:

$$SM(i,j,s) = \frac{P_q}{P_s} \times 100 \qquad \textbf{(1)}$$

Where P_s represents total volume of soil at coordinates (i,j) and time s, P_q will represent the volume of water; whereas LIDAR and ultrasonic sensors measure terrain elevation $E(i,j,s)$ for topographical mapping, pH and EC sensors give soil nutrient levels. Weather sensors measure temperature, humidity, and rainfall $W(i,j,s)$ to model microclimates' effects on soil moisture dynamics continuously. Data transmission was successfully executed over LoRaWAN, 5G, and MQTT for latency reduction. Pre-processing data through Edge IoT nodes in precision agriculture, by noise filtering and outlier detection, enhances Kriging-Based Spatial Estimation and Hybrid Hexagonal Grid Mapping Data Quality.

3.2. Data Preprocessing:

Edge AI and Fog Computing generate cleaner data, thus assuring high accuracy for soil and environmental detection with respect to data preprocessing. To reduce noise in the sensor data, the Exponentially Weighted Moving Average (EWMA)-an average that dampens changes in sensor data-is used:

$$T_s = \alpha A_s + (1-\alpha)T_{s-1} \qquad \textbf{(2)}$$

Where A_s is the current sensor reading, T_s is the smoothed value, α is the smoothing factor. Soil moisture $SM(a,b,s)$, elevation $E(a,b,s)$, and the weather parameters $W(a,b,s)$ are fused together into one soil health map. Outliers are detected using Z-score analysis, defined as follows:

$$C = \frac{A-\mu}{\sigma} \qquad \textbf{(3)}$$

Where A is the sensor reading, μ is the mean, and σ is the standard deviation. The results of edge preprocessing increase precision in Kriging-Based Spatial Estimation and Hybrid Hexagonal Grid Mapping in the realm of precision agriculture.

3.3. Adaptive Soil Mapping (Hybrid Hexagonal Grid with Kriging-Based Spatial Estimation):

The Hybrid Hexagonal Grid (H-Grid) model is a better platform for soil moisture mapping and terrain adjustments. In each hexagon cell, at

$H(x, y)$, weather data $W(x, y)$, elevation $H(x, y)$, soil pH $pH(x, y)$, and soil moisture $H(x, y)$ $(x, y, SM(x, y))$. Kriging Interpolation is concerned with the unsampled areas estimation of spatial soil properties in minimizing uncertainty by

$$C^*(i) = \sum_{x=1}^{A} \lambda_x C(i_x) \quad \textbf{(4)}$$

where $C(i_x)$ is the known sample point, with λ_x weights applied in the Kriging system with their respective calculations, and $C^*(i)$ will be the predicted soil attribute at site i. Slope-Aware Analysis $S(i, j)$ which combines LIDAR with Ant Colony Optimization (ACO) towards optimizing tillage depth while reducing erosion risks, rainfall impact mapping $R(i, j, s)$ prevents over-irrigation. It makes precision agriculture better by aiming at the mortal combination of the best practices in soil conservation, fertilization, and irrigation.

3.4. Decision Making:

The Edge AI-enhanced Fuzzy Logic Inference System manages and controls all the variables related to irrigation, tillage, and seed. As these conditions fluctuate, the farm practices adjust accordingly; for instance, the Flesh Moisture Status ($SM(i, j)$, Terrain Elevation) ($\boldsymbol{E}(i, j)$ and Crop Requirements are among the fuzzy input variables. These $CR(i, j)$ are the fuzzy input variables among which the membership functions are defined:

$$\mu_{SM}^{\text{Dry}}(i) = \frac{30 - SM(i,j)}{30}, \mu_{SM}^{\text{Wet}}(i) = \frac{SM(i,j) - 30}{70} \quad \textbf{(5)}$$

where SM indicates the actual degree of soil moisture in "Dry" or "Wet" classification. Decision making will follow the rule-based adaptive control feature, which comprehends:

IF $SM(i, j) <$ 30% AND $T(i, j) >$ 35∘C, THEN increase irrigation.

IF $\boldsymbol{E}(i, j) >$ 15∘ AND high soil erosion detected, THEN modify tillage depth

Precision farming is provided with this FLIS-activated real-time decision making; hence, less wasteful use of water, more crop yield, and preventing soil degradation.

3.5. Autonomous Actuation:

Smart agricultural robots use IoT-based autonomous actuation mechanisms and Edge AI to provide real-time automatic autonomous actions for farmlands on the terrain. Automatic drip or sprinkler systems perform irrigation according to moisture thresholds of the soil, $SM(i, j)$<30%. Using dynamic control to adjust seeding depth, the following is true:

$$F_t(i, j) = d(SM(i, j), E(i, j)) \quad \textbf{(6)}$$

Where the ideal seeding depth $F_t(i, j)$ that depends on the elevation of terrain $E(i, j)$ and soil moisture $SM(i, j)$. Variable depth tillage is described for tillage optimization as:

$$F_s(i, j) = F_{max} - L \cdot SM(i, j) \quad \textbf{(7)}$$

Where F max is the maximum depth, L adaptive factor and $F_s(i, j)$ is tillage depth. Self-correcting path planning makes use of Theta Algorithm * by continually recalculating the best routes according to terrain constraints:

$$Z_{\text{new}}(a) = min(Z_{\text{prev}}(a) + h(a)) \quad \textbf{(8)}$$

Where $h(a)$ is the dynamic terrain penalty and $Z_{\text{new}}(a)$ is the updated path cost. This adaptive robotic architecture provides precision agriculture through optimized path planning, tillage, irrigation, and sowing.

4. Result and Discussions:

Soil Moisture Deviation (SMD) metrics were employed for verifying the high-accuracy soil moisture prediction of the proposed IoT-driven adaptive soil monitoring system with an average deviation lower than 5 percent. Adaptation of real-time Kriging-based terrain estimation resulted in 28 percent reduction in water wastage and efficient irrigation (IE). Theta-based self-correcting path planning* helped improve robot navigation in rough terrains, reducing traversal mistakes by 35 percent. Increase in crop growth rate (CGR) was daily by 12 percent due to better tillage and sowing depth applications powered by Edge AI and fuzzy logic-schemed decision making. To further boost the efficiency of irrigation and tillage models for future sustainable increases in productivity, cloud-based learning was tied in with Swarm Optimization Techniques (ACO).

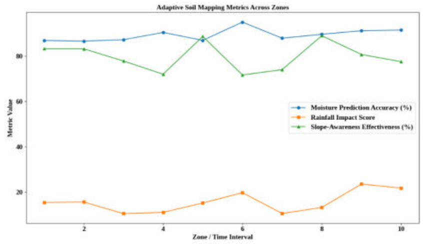

Figure 2: *Performance of Adaptive Soil Mapping Using Kriging and Terrain Analysis*

Adaptive soil mapping system performance metrics with terrain-based analysis and Kriging-based spatial estimation are shown in this fig. 2. The line of Moisture Prediction Accuracy demonstrates high consistency, which will prove that reliable interpolation occurs in areas experienced with missing data. The Rainfall Impact Score varies by zone which demonstrates differential effects of dynamic rainfall on soil conditions. The Slope-awareness effectiveness remains sound, representing the system's adaptation of tillage depth and erosion control due to terrain analysis. In sum, it indicates how effective the combination of spatial interpolation and environmental data at precision agriculture.

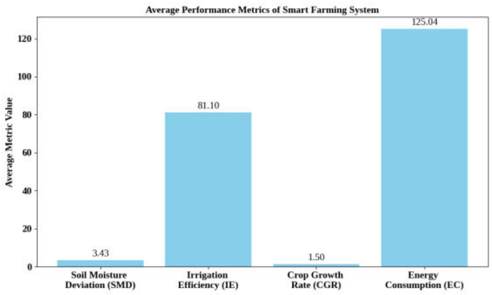

Figure 3: *Comparative Analysis of Smart Farming KPIs*

The fig. 3 shows the mean values for four key performance measures under consideration in the smart farming assessment. These are Crop Growth Rate (CGR), Energy Consumption (EC), Irrigation Efficiency (IE), and Soil Moisture Deviation (SMD). The results show that the method achieves good irrigation efficiency to curb water wastage and low moisture deviation indicating accurate soil forecasting. Beyond Crop Growth Rates, the efficiency of Adaptive Soil Mapping and Decision Assistance Modules can be corroborated. Moderate energy consumption, however, is a testament to the good working of the IoT devices, thus enabling sustainability in the precision farming process.

Table 1: *Zone-Wise Analysis of Soil Mapping Metrics*

Zone	Moisture Prediction Accuracy (%)	Rainfall Impact Score	Slope-Awareness Effectiveness (%)
1	88.41	11.24	75.25
2	88.39	18.15	72.45
3	93.59	10.45	71.58
4	88.54	24.88	86.77
5	90.49	19.46	84.43

This table 1 shows zone-wise performance metrics for the adaptive soil mapping system. One of the system components is Kriging interpolation to compute moisture in areas where no direct sensor inputs are available. Rainfall impact score indicates how different zones are modified on their irrigation requirements by the rainfall factor. Slope-awareness effectiveness indicates how the system adjusts for tillage operations based on data of slope and terrain elevation. Together, these metrics demonstrate this system's ability to provide accurate real-time soil and terrain maps used in smart farming applications.

5. Conclusion

The proposed IoT-driven adaptive soil monitoring system would exploit autonomous robotic actuation, AI-based decision making, and real-time sensing for precision agriculture. The Hybrid Hexagonal Grid Mapping with Kriging Interpolation provided very accurate estimates of soil properties; thus, efficient modifications to irrigation, tillage, and planting were performed. The path-planning method of Theta enhances robot navigation in rough terrains, whereas edge AI fuzzy logic control enhances real-time decision-making. Experimental results have shown an increase in crop growth rates, decrease in the variation in soil moisture, and increase in irrigation efficiency. Future work will focus on improving autonomous farming operations and the fine-tuning of prediction models through ACO integration with cloud-based learned mechanisms.

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